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Neural correlates of flow, boredom, and anxiety in gaming: An electroencephalogram study

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NEURAL CORRELATES OF FLOW, BOREDOM, AND ANXIETY IN GAMING: AN ELECTROENCEPHALOGRAM STUDY

by

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ABSTRACT

Games are engaging and captivating from a human-computer interaction (HCI) perspective as they can facilitate a highly immersive experience. This research examines the neural correlates of flow, boredom, and anxiety during video gaming. A within-subject experimental study (N = 44) was carried out with the use of electroencephalogram (EEG) to assess the brain activity associated with three states of user experience – flow, boredom, and anxiety – in a controlled gaming environment. A video game, Tetris, was used to induce flow, boredom, and anxiety. A 64 channel EEG headset was used to track changes in activation patterns in the frontal, temporal, parietal, and occipital lobes of the players' brains during the experiment. EEG signals were pre-processed and Fast Fourier Transformation values were extracted and analyzed. The results suggest that the EEG potential in the left frontal lobe is lower in the flow state than in the resting and boredom states. The occipital alpha is lower in the flow state than in the resting state. Similarly, the EEG theta in the left parietal lobe is lower during the flow state than the resting state. However, the EEG theta in the frontal-temporal region of the brain is higher in the flow state than in the anxiety state. The flow state is associated with low cognitive load, presence of attention levels, and loss of self-consciousness when compared to resting and boredom states.

Keywords: Electroencephalogram, Fast Fourier Transformation, Flow, Frontal, Parietal, Occipital, Frontal-Temporal, Human-Computer Interaction, Mid-Beta, Theta, Alpha, Neural Correlates

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TABLE OF CONTENTS

Page

LIST OF ILLUSTRATIONS

LIST OF TABLES

1. INTRODUCTION

Computer games, being interactive in nature, have been actively adopted and enjoyed by people irrespective of their age group and background. From the Human-Computer Interaction (HCI) perspective, games are captivating and engaging as they form an ideal ground for interactivity and communication (Hartmann & Klimmt, 2006). There has been a growing interest in HCI to understand user states of experience and the design of applications with dynamic user experience (UX) as its core (McCarthy & Wright, 2004; Jacko, 2012). Video games, with their ability to draw people in, can generate different user experiences while gaming. In a gaming context, cognitive and emotional states generated by dynamic gaming conditions can lead players to be happy, cognitively efficient, intrinsically motivated, fully focused, and in control of the total gaming environment (Cowley et al., 2008; Moneta & Csikszentmihalyi, 1999).

Games with incremental difficulty levels and an immersive nature provide the opportunity to decide, take actions, and influence the gameplay. According to the flow and emotion theories, if the skills of a person meet the challenge of a task, then strong involvement in a task can be observed (Cowie et al., 2001). The challenge level in the gameplay is related to sensorimotor abilities and cognitive challenges (Ermi & Mäyrä, 2005). Csikszentmihalyi (1975, 1990, 1997) identified three main states of user experience based on challenge and skill: boredom, flow, and anxiety. Boredom is a state when the challenge is much lower than skill. A state of flow or optimal experience emerges when the difficulty of a task at hand and the skills of a player are balanced (Jackson, 1992; Millan et al., 2004; Moneta & Csikszentmihalyi, 1999; Okada, 1993).

Anxiety occurs when the challenge is much greater than the skill (Moneta & Csikszentmihalyi, 1999).

As illustrated in Figure 1.1, a player can be engaged in gaming, and potentially experience various states of user experiences such as boredom, apathy, absorption, flow, frustration, and anxiety, based on the challenge of the game and the player's ability (Massimini & Massimo, 1988). Sometimes, people find games so deeply captivating that time flies during gaming and they do not even notice their surroundings (Agarwal & Karahanna, 2000). During that period of engagement and absorption, most or all of their attention is on the game. Such a state has been called "in the game" (Jennett et al., 2008) or "in the zone" (Marr, 2001). Assessing such user states of experience (i.e., those presented in Figure 1.1) is important because it provides designers, developers, and usability specialists with opportunities to improve the user experience. Such assessments have been widely used in the field of HCI, an evolving research field that studies user experience with a product, system, or an application (Tondello, 2016). More information on assessing various user states of experience based on the challenge and abilities has been presented in Figure 1.1 will be discussed in Section 2 which covers the literature review. The most common and traditional approaches to assess user experience are self-reported measures (e.g., questionnaires and interviews) that are typically retrospective in nature and are subjected to biases, such as social desirability and recall biases (Bhattacherjee, 2012). With advancements in technology, alternative approaches are available that can assess user experience in real-time. One such approach is electroencephalogram (EEG). Unlike traditional approaches, EEG can provide continuous and concurrent assessments of user experience without having to interrupt the user. EEG can be used to capture spontaneous brain activity associated with constructs related to or in the context of information systems (IS), such as cognitive workload, emotion, and user states of experience, that can be used to develop neuro-adaptive IS (Müller et al., 2015). EEG technology is still relatively new and underexplored in the context of HCI, and more research is needed to relate EEG activities to specific states of user experience. This research is a step in this direction - it aims to identify EEG correlates for user experience: flow, boredom, and anxiety.

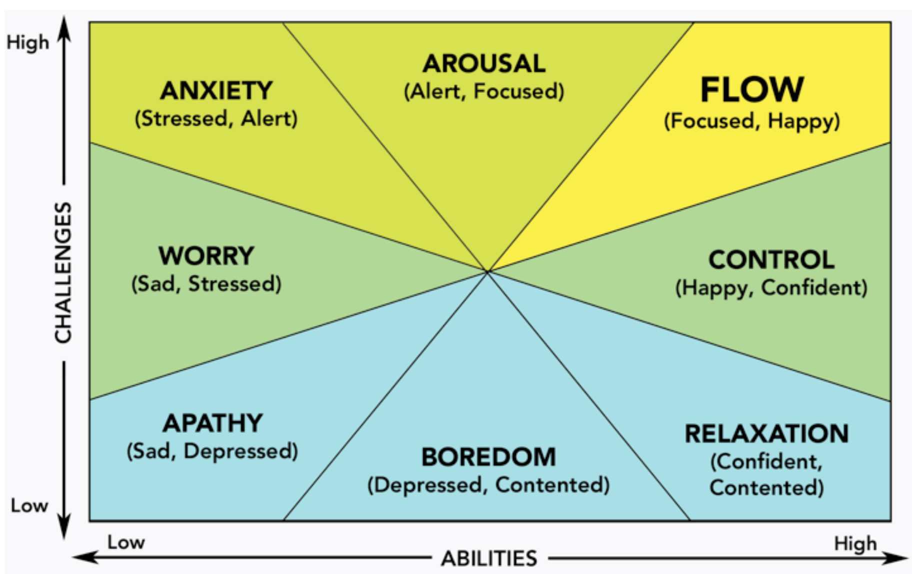


Figure 1.1. Experience Fluctuation Model Related to Challenges and Abilities, adopted from Massimini & Massimo (1988)

Given the need to understand the importance of optimal experience in HCI in the gaming context, and the potential of EEG to provide a better and more reliable way of assessing user experience, our research question is:

Research Question: What are the neural correlates of flow, boredom, and anxiety in the gaming context?

Although EEG has been used in the medical area for decades, its applications in HCI are emerging and very promising (Van Erp et al., 2012). EEG can be used to assess the real-time experience of users and can provide continuous assessments of user states in HCI. It has the potential to provide more reliable and objective (i.e., less subjective) assessments than self-reported assessments of user experience (Berka et al., 2007).

The rest of the paper is organized as follows: Section 2 provides a review of the related literature. Section 3 provides the theoretical foundation for the research hypotheses. Section 4 describes the research methodology, and Section 5 presents the data analysis procedure and the results. Section 6 discusses the results. Section 7 provides the limitations of the research as well as future research directions. Section 8 highlights the theoretical and practical implications, and Section 9 concludes the paper.

2. LITERATURE REVIEW

In this section, the background work related to flow, boredom, and anxiety is reviewed. Research studies that have utilized a variety of qualitative and quantitative techniques to capture and understand the above-mentioned user states are reviewed as well. The importance of Brain-Computer Interface (BCI) and EEG research in NeuroIS and HCI fields is also discussed. In addition, this chapter discusses and summarizes previous studies' findings related to neural and physiological correlates of the above three user states.

2.1. FLOW STATE AS OPTIMAL EXPERIENCE

Csikszentmihalyi (1990) conceptualizes the state of flow as an optimal experience. He also theorizes nine components for flow: balance of challenge and skill, clear goals, immediate feedback, perceived total control, loss of self-consciousness, focused concentration, time distortion, merging of action and awareness, and autotelic experience. These nine components of the flow state are summarized in Table 2.1.

Flow, which is the optimal state of experience, is defined as a "holistic sensation that people feel when they act with total involvement" (Csikszentmihalyi, 1975, p. 36). Flow occurs when an individual is completely engaged and involved in a task or a system, giving an immersive experience of being 'in the zone' (Fang et al., 2013). A person in the flow state experiences focused attention, time distortion, intrinsic motivation, perceived control, merging of action and awareness, and loss of self-consciousness (Csikszentmihalyi, 1990; Csikszentmihalyi & LeFevre 1989).

Table 2.1. Components of the Flow State (Csikszentmihalyi, 1990)

Dimension	Description
Balance of challenge and skill	A key aspect of the state of flow is that the skill of the individual and the challenge of the activity need to be in balance with each other.
Clear goals	The goals/objectives of the task or activity must be clear and unambiguous.
Immediate feedback	The performance feedback on the task or activity should be clear, immediate, and unambiguous.
Control	The individual perceives control of his/her actions and the environment.
Loss of self-consciousness	Because of the pre-occupied activity, the individual “loses” oneself and experiences a sense of separation from the world around him/her.
Concentration on the task at hand	The individual pays complete attention to the task or activity, such that all other distractions are blocked out from his/her awareness.
Transformation of time	Time no longer seems to pass the way it normally does. The individual loses track of time and the perception of time is distorted.
Merging of action and awareness	The individual is so involved in the activity that his/her actions become spontaneous or automatic responses.
Autotelic nature	The activity that consumes the individual is intrinsically rewarding and motivating to him/her.

For one to get into the flow state, not only should there be a balance of challenge and skill, but it is also necessary to have clear goals as well as immediate and unambiguous feedback. A deep level of involvement in gameplay can arise when the skill level of a player matches the challenge level of the game, and the goals and feedback are clear (Csikszentmihalyi 1990; Lee et al., 2015; Nah et al., 2011). The flow state is characterized by total control over the task, loss of consciousness of oneself and the physical environment, focused attention and concentration on the task at hand, distortion or transformation of time, merging actions with awareness (i.e., actions become automatic and effortless), and autotelic (i.e., intrinsically rewarding) experience. Thus, balance of challenge and skill, clear goals, and immediate feedback are regarded as necessary conditions for flow, and the remaining components describe the flow experience.

According to the flow theory, the relationship between skill and challenge lays the foundation for the psychological state of flow (Csikszentmihalyi, 1990, Guo et al., 2016; Nah et al., 2010). Challenge is considered as an opportunity to perform an action, and skill is the capability to perform that action. When the goals are clear, and the feedback is immediate and unambiguous, the congruence between challenge and skill can give rise to the necessary conditions for the flow state. As presented in Figure 2.1, the flow channel can be explained as a function on a plane with skills and challenges as axes (Csikszentmihalyi, 1975) and is considered as the challenge/skill balance model. An increase in the user’s skill can arise from learning, and an increase in the challenge of performing an activity could be due to novelty or increased difficulty; flow experience can be attained by maintaining a balance between the skill and the challenge (Cowley et al., 2008; Csikszentmihalyi, 1975; Goleman, 1995). A person who is in the flow state is completely immersed and absorbed in the activity to the point where nothing else seems to matter Csikszentmihalyi, 1975). In other words, ‘‘people [who are in flow] are willing to perform an activity for their own sake, with little concern for what they get out of it’’ (Csikszentmihalyi, 1990, p. 71).

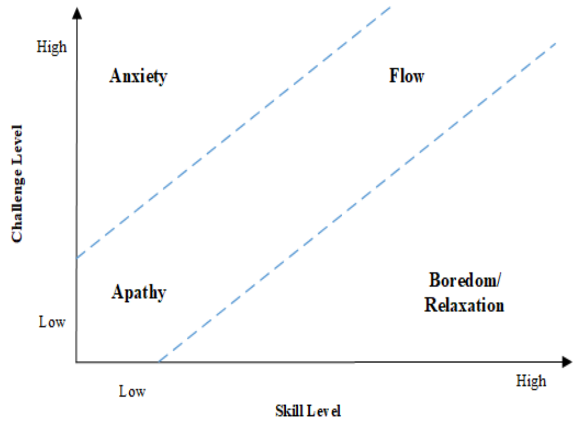


Figure 2.1. The Challenge/Skill Balance Model adopted from Csikszentmihalyi & Csikszentmihalyi (1992)

Table 2.2 summarizes the key components of flow, and its related construct, cognitive absorption, in the IS literature (HCI context). Agarwal and Karahanna proposed the construct, cognitive absorption, based on the concepts of flow, absorption, and cognitive engagement (Agarwal & Karahanna, 2000). They defined cognitive absorption as a state of deep involvement with software and conceptualized it using five dimensions: curiosity, control, temporal dissociation, focused immersion, and heightened enjoyment. Several other terms, such as immersion and presence, have also been used by researchers in other disciplines to capture the flow phenomenon (Csikszentmihalyi, 1990; Lombard & Ditton, 1997, Qin et al., 2009). For example, Qin et al. (2009) described immersion as an intense experience where a user is involved both mentally and physically in a given task. They identified seven components for immersion, which are curiosity, concentration, challenge and skill, control, comprehension, empathy, and familiarity. Lombard and Ditton (1997) provided six conceptualizations for presence as social richness, realism, transportation, immersion, social actor within a medium, and medium as a social actor. Presence has also been represented as "the perceptual illusion of non-mediation" (Lombard & Ditton, 1997, p. 755). Hence, presence (or telepresence) is also closely related to and an important aspect of the flow construct (Chen, 2006; Lee & Chen, 2010; Nah et al., 2011; Skadberg & Kimmel, 2004).

Table 2.2 highlights components of the flow and cognitive absorption constructs, which are terms that have been commonly used by the IS research community. As shown in Table 2.2, there have been variations across researchers' conceptualizations and operationalizations of the flow and cognitive absorption constructs.

Table 2.2. Components of Flow in the HCI Context

Reference	Flow Components	Research Method	Research Setting
Agarwal & Karahanna (2000)	Curiosity, control, temporal dissociation, focused immersion, heightened enjoyment	Survey questionnaire	IT usage
Chen (2006)	Telepresence, time distortion, concentration, loss of self-consciousness, a clear goal, control, immediate feedback, merging of action and awareness, positivity of affect, enjoyable feelings	Survey questionnaire	Web navigation
Chen, Wigand, & Nilan (1999)	Merging of action and awareness, concentration, control	Survey questionnaire	Web navigation
Chen, Wigand, & Nilan (2000)	Merging of action and awareness, concentration, loss of self-consciousness, time distortion, control, telepresence, enjoyment, challenge	Survey questionnaire	Web navigation

Table 2.2. Components of Flow in the HCI Context (cont.)

Cowley, Charles, Black, & Hickey (2008)	Challenge, immersion, control, concentration, clear unambiguous goals, immediate feedback, lose consciousness of passage of time, lose sense of identity	Conceptual and literature review	Video game
Fang, Zhang, & Chan (2013)	Balance of challenge and skill, clear goals and feedback, concentration, control, immersion (loss of self-consciousness, merging of action and awareness, time transformation), autotelic experience	Survey questionnaire	Computer game
Fu, Su, & Yu (2009)	Concentration, goal clarity, feedback, challenge, autonomy, immersion, social interaction, knowledge improvement	Survey questionnaire	E-learning games
Ghani & Deshpande (1994)	Enjoyment, concentration	Survey questionnaire	Computer use
Guo & Poole (2009)	Perceived web complexity, balance of challenge and skill, goal clarity, feedback, concentration, control, merging of action and awareness, transformation of time, transcendence of self, autotelic experience	Experiment and questionnaire	Online shopping
Guo, Xiao, Van Toorn, Lai, & Seo (2016)	Balance of challenge and skill, clear goals, immediate feedback, telepresence, concentration, loss of self-consciousness, control, time distortion	Survey questionnaire	Online learning
Hoffman & Novak (1998)	Challenge, skill, balance of challenge and skill, interactivity, vividness, telepresence, focused attention, involvement	Conceptual and literature review	Web navigation

Table 2.2. Components of Flow in the HCI context (cont.)

Hoffman & Novak (2009)	Challenge, skill, interactivity, vividness, telepresence, usage, involvement, motivation, attention, ease of use, positive subjective experience, control, exploratory behavior, curiosity, discovery, attractiveness, novelty, playfulness, personal innovativeness, content	Conceptual and literature review	Online marketing
Jiang & Benbasat (2004)	Control, attention focus, cognitive enjoyment	Experiment and questionnaire	Online shopping
Lee & Chen (2010)	Concentration, enjoyment, time distortion, telepresence	Survey questionnaire	Online shopping
Li & Browne (2006)	Focused attention, control, curiosity, temporal dissociation	Survey questionnaire	Web navigation
Nah, Eschenbrenner, & DeWester (2011)	Telepresence, enjoyment	Experiment and questionnaire	Virtual world
Nah, Eschenbrenner, Zeng, and, Telaprolu, & Sepehr (2014)	Balance of challenge and skill, clear goals, immediate and unambiguous feedback, concentration, sense of control, loss of self-consciousness, merging of action and awareness, time distortion, immersion, telepresence, exploratory behavior, playfulness, sense of identity, social interaction, intrinsic motivation, autotelic experience, enjoyment, curiosity, heightened state of ability, feeling of pressure	Conceptual and literature review	Video game
Nel, Van Niekerk, Berthon, & Davies (1999)	Control, attention focus, curiosity, intrinsic interest	Experiment and questionnaire	Web navigation

Table 2.2. Components of Flow in the HCI context (cont.)

Pace (2004)	Joy of discovery and learning, reduced awareness of physical surroundings, time distortion, merging of action and awareness, control, mental alertness, telepresence	Interview	Web navigation
Saade & Bahli (2005)	Temporal dissociation, focused immersion, heightened enjoyment	Survey questionnaire	Online learning
Seger & Pottts (2012)	Concentration, merging of action and awareness, little/no self-consciousness, skills meet challenges, time passes quickly, intrinsically rewarding, unique sensations, sense of invincibility, increased physical strength, time passes slowly, calm relaxation, attention	Survey questionnaire	Video game
Siekpe (2005)	Challenge, concentration, curiosity, control	Survey questionnaire	Online shopping
Skadberg & Kimmel (2004)	Time distortion, enjoyment, telepresence	Survey questionnaire	Web navigation
Sweetser & Wyeth (2005)	Concentration, challenge, skill, control, clear goals, feedback, immersion, social interaction	Expert review	Computer game
Trevino & Webster (1992)	Control, attention focus, curiosity, intrinsic interest	Survey questionnaire	Email, Voice mail
Wang, Liu, & Khoo (2009)	Balance of challenge and skill, merging of action and awareness, clear goals, immediate feedback, concentration, control, loss of self-consciousness, time distortion, autotelic experience	Survey questionnaire	Internet gaming
Webster, Trevino, & Ryan (1993)	Control, attention focus, curiosity, intrinsic interest	Survey questionnaire	Online learning and email

Table 2.2. Components of Flow in the HCI context (cont.)

Zaman, Anandarajan, & Dai (2010)	Intrinsic enjoyment, concentration	Survey questionnaire	Instant messaging

Outside the IS context, Jackson and Marsh (1996) developed a scale, known as the flow state scale (FSS), that is based on all nine components of flow proposed by Csikszentmihalyi (1990). This scale has been used to capture the flow experience of athletes as a state, i.e., for a particular event. Among the nine components of flow, it was found that control, balance of challenge and skill, concentration, and autotelic nature of experience contributed more to the flow experience of athletes when compared to transformation of time and loss of self-consciousness (Jackson & Marsh, 1996). In contrast to the FSS that assesses flow as a state, a dispositional flow scale (DFS) was later developed by Jackson et al. (1996) to assess the flow experience of athletes as a trait, i.e., based on the frequency of flow experiences. Jackson and Eklund (2002) also developed an improved version of the FSS and DFS (i.e., with regard to measurement of some of the flow components) and named them the flow state scale-2 (FSS-2) and dispositional flow state-2 (DFS-2) respectively.

Two published papers in the IS domain have operationalized Csikszentmihalyi’s (1990) nine components of flow and assessed them in the IS context. Fang et al. (2013) conceptualized clear goals and feedback as one component and developed an instrument that took into account all the flow components proposed by Csikszentmihalyi (1990) to capture users’ flow experience in a computer gaming context. Using responses from 260 participants to carry out a factor analysis, six components emerged: clear goals and feedback, focused immersion (i.e., loss of self-consciousness, merging of action and awareness, transformation of time), balance of challenge and skill, autotelic experience, concentration, and control. Another study by Wang et al. (2009) utilized the DFS-2 to capture users' flow experience in Internet gaming. One thousand five hundred and seventy-eight participants completed the questionnaire. The results suggest that the DFS-2 has acceptable reliability estimates and convergent validity. Research that has assessed and validated the FSS-2 or a scale comprising the nine components proposed by Csikszentmihalyi (1990) in an IS context is still lacking. Fang et al. (2013) found the flow construct to load onto six instead of nine components. Given the importance of triangulating assessments or measurements of the flow construct in IS research, we examine an alternative measurement approach that uses EEG to capture users' flow experience in this research.

Bruya (2010) conceptualized the flow state using a new perspective in the cognitive science of attention and action, and suggested that the flow state results in effortless attention. In other words, when a person is in the flow state, he or she maintains a sustained level of efficiency such that increased task demands can be carried out with no increase in felt effort because of the high level of focus, control, and automaticity achieved in the flow state (Bruya, 2010). When one's attention and action are merged in the flow state, the action becomes automatic and seemingly effortless. Hence, the flow state has been associated with effortless attention and action, which are key aspects of autotelic experience (Bruya, 2010).

2.2. DEFINITION AND CORRELATES OF BOREDOM STATE

The boredom state can occur due to a mismatch between the challenge and skill levels (Csikszentmihalyi, 1975, 1990). Boredom has been termed as a state of disinterest (Fahlman et al., 2013). Task-unrelated thoughts tend to develop during boredom which ultimately lead to attentional failures (Danckert & Merrifield, 2016). Researchers conceptualized the state of boredom based on four major theories: arousal, attention, psychodynamic, and existential theories. According to Leswinsky (1943), a psychodynamic psychologist named Theodor Lipps considered boredom as a feeling of unpleasantness generated due to a need that is unfulfilled for psychic stimulation. Fenichel (1951) explained that the unfulfillment can occur not only due to a lack of stimulation, but it can also occur if the state of mind prevents an individual from engaging in a simulated activity. According to existential theories, “emptiness following feelings of meaninglessness” can also lead to boredom (Frankl, 1992, p. 104). In the view of arousal theorists, boredom occurs due to a mismatch between the required arousal level and the arousal level triggered by the simulated environment (O’Hanlon, 1981); for example, cognitivists consider boredom as a less inspiring environment that leads to a decreased ability to concentrate. (Fisherl, 1993). According to the attentional theories, boredom is caused by failure of the attentional processes, resulting in an inability to achieve focused attention or engagement (Fisherl, 1993; Schur, 1969).

Mikulas and Vodanovich (1993) provided the following definition for the boredom state: “a state of relatively low arousal and dissatisfaction, which is attributed to an inadequately stimulating situation” (p. 3). However, the definition of boredom defined by Eastwood and colleagues, which is most commonly used, is as follows: “an aversive state of wanting, but being unable, to engage in satisfying activity" (Eastwood et al., 2012, p. 482). When one is bored in performing a task, the aversive state (not able to engage oneself in a satisfying activity) arises, resulting in a need to pursue a different goal (look for something different); in such cases, boredom is seen as an emotional cue. More specifically, Bench & Lench (2013) indicated that boredom "might arise during times when goals are blocked". Fisher (1993) defines boredom as "a transient affective state in which the individual feels a pervasive lack of interest in the current activity" (p. 3); Csíkszentmihályi views boredom as a state in which the skills of a player are greater than the simulated challenge (see Figure 2.1) (Balducci et al., 2017; Csíkszentmihályi, 1992).

Various researchers focused mainly on low/under stimulation tasks to understand the boredom state. For example, although inspection and continuous control (i.e., driving, tracking, piloting, etc.) tasks are repetitive and less stimulative in nature, they demand attention. It has been concluded that a task with prolonged exposure not only induces boredom but also reduces physiological arousal. All the above-mentioned theories suggest that the central feature of boredom is the apathetic experience of wanting but being unable to engage in stimulating and satisfying activities (Berlyne, 1960; Mikulas & Vodanovich, 1993; Sundberg et al., 1991). Boredom is often conceptualized as an aversive state of under arousal that occurs when "information" or environmental "stimulation" is redundant, monotonous, of low intensity, or meaningless (Geiwitz, 1966, Hebb & Donderi, 2013). While playing video games, the cognitive actions that are less differentiating and more homogenous in nature give rise to boredom (Perkins & Hill, 1985). Therefore, a combination of low goal-directed task followed by a decline of interest can cause boredom. Slow perception of time is also considered as a consistent correlate of boredom (Bench & Lench, 2013). In addition, individuals who have high boredom proneness are more likely to overestimate the amount of time spent on the task whereas individuals with low boredom proneness are more likely to underestimate the elapsed time (Danckert & Allman, 2005). Boredom is a common state/phenomenon experienced by the majority in daily routines. Despite its importance and significant potential social and psychological consequences, it is still poorly understood (Eastwood et al., 2012). Based on previous research studies, the correlates of boredom are low attention, low arousal, slowed time perception, and task-unrelated thoughts.

An attempt that has been made to find a way to maintain optimal challenge revealed that physiological correlates can be used to classify affective states (Rani et al., 2005). Galvanic Skin Response (GSR), a measure of skin resistance (physiological signal), decreases with an increase in the task difficulty (Chanel et al., 2008). A research study using EEG conducted by Plotnikov et al. (2012) confirmed that EEG oscillations can classify different user states. Fahlman et al. (2013) developed and validated a full-scale measurement of the boredom state - Multidimensional State Boredom Scale (MSBS) (Fahlman et al., 2013). The scale consists of mentioned factors: perception of time, high and low arousal, inattention, and disengagement. The MSBS scores correlate higher with the following boredom measures: impulsivity, inattention (i.e., low arousal), and disengagement. Physiological and EEG signals have been captured in the literature to test and classify the user states –flow, boredom, and anxiety – but their correlates over specific regions of the brain were least explained. A few studies have attempted to understand the neural correlates of the boredom state using fMRI and they found that the frontal and parietal lobes were active during boredom (Ulrich et al., 2014; Mathiak et al., 2013; Andrews-Hanna, 2012; Buckner et al., 2008; refer to Section 2.6.2 for more information). When the neural dynamics of boredom were investigated using fMRI, activation over Dorsolateral Pre-Frontal Cortex (DLPFC) was recorded (Tabatabaie et al., 2014). To the best of our knowledge, no study to date has specifically investigated the neural correlates of boredom over the frontal lobes in the gaming context.

2.3. STATE OF ANXIETY AND COGNITIVE PERFORMANCE

Anxiety is considered as an unpleasant motivational and emotional state occurring under threatening circumstances. The state of anxiety can be described as a situational stress aroused by the environment (Eysenck, 1992). It has been conceptualized as “a state in which an individual is unable to instigate a clear pattern of behavior to remove or alter the event/object/interpretation that is threatening an existing goal” (Dalgleish & Power, 1999, pp. 206–207). Clinical anxiety (i.e., anxiety as a personality dimension or trait) has been researched with high priority and importance compared to the state of anxiety experienced by the normal population. In earlier research studies, anxiety was assessed by trait anxiety measures such as Spielberger’s State–Trait Anxiety Inventory (Spielberger et al., 1983). Later studies identified anxiety as a state that can be experimentally induced to assess differences among individuals. During the state of anxiety, individuals worry about the current goal and try to develop effective strategies to reduce anxiety in order to achieve their goal.

Processing Efficiency and Attentional Control theories, which will be explained later, have been used to explain the state of anxiety (Eysenck et al., 2007). It is crucial to understand the state of anxiety with respect to performance and cognition due to its adverse effects on the performance of cognitive tasks (Eysenck, 1992). To identify the cognitive processes associated with the state of anxiety, researchers have used short-lasting cognitive tasks to study cognitive processes under controlled conditions. Csikszentmihalyi (1990) stated that the state of anxiety occurs when the challenge of a given task is greater than the skill of an individual (see Figure 2.1.1) (Csikszentmihalyi, 1990).

Processing efficiency theory focuses on differentiating efficiency and effectiveness, and states that the negative effects of anxiety are greater on efficiency than effectiveness (Eysenck, 1992). Two main effects of anxiety are that: (1) it can consume most of the working resources for attention and limit concurrent processing of tasks; (2) it can enhance motivation in order to minimize the anxiety level (Borkovec, 1994; Sarason, 1988; Eysenck, 1992). Researchers assume that anxiety can affect primarily those regions of the brain that are involved in central executive processes (Rapee, 1993). Although the processing efficiency theory attempted to explain the effects of anxiety on central executive processes, it did not identify the processes that are affected by the anxiety state. For example, the central executive regions fulfill certain functions like focusing attention on relevant tasks, inhibiting attention on irrelevant tasks, planning sub-tasks to achieve a goal, and switching attention between tasks (Smith & Jonides, 1999). Interestingly, a few studies have shown no difference in performance between participants of high- and low-anxiety levels (e.g., Blankstein et al., 1990; Blankstein et al., 1989; Calvo et al., 1990; Calvo & Ramos, 1989).

Attentional Control Theory focuses on cognitive performance and anxiety (Yantis, 1998). According to attentional control theory, anxiety destroys the balance between stimulus-driven attentional system and goal-directed attentional system (Fox et al., 2005). This theory also supports the notion that anxiety impairs attentional control which is a key function in performing a cognitive task. In other words, an anxious individual preferentially allocates attentional resources to threat related stimuli either internally or externally (Sarason, 1988). However, the theoretical explanations provided by processing efficiency and attention control theories were considered oversimplified. Researchers believed it is difficult to operationalize high levels of executive functions and goal-directed planning process. According to previous studies, the relationship between the anxiety state and cognitive task performance can be better understood with brain imaging techniques when compared to self-reported measures, incentive manipulations, and physiological measures (Spielberger et al., 1983; Dornic, 1977, 1980; Ansari & Derakshan, 2011). Brain Imaging studies that are focused on attention shifting and inhibition processes revealed that prefrontal areas of the brain are involved in central executive functions (Collette & Van der Linden, 2002). The affects and correlates of the anxiety state will also be discussed in Section 2.6.3.

2.4. BRAIN COMPUTER INTERFACE – EEG FOR NEURO-IS

The potential of cognitive neuroscience gains visibility in the social sciences because of its ability to link human behavior to brain activity (Glimcher & Rustichini, 2004). Advances in cognitive neuroscience help in creating an understanding of the brain activity involved in mental processes. Brain Computer Interface (BCI) devices provide direct communication between the brain and external electrical devices to capture rich information about the user states of experience while interacting with a system or playing games (Lee & Tan 2006; Tan & Nijholt, 2010). They are often used for researching, mapping, assisting, and repairing sensory-motor or human cognitive functions (Krucoff et al., 2016).

Compared to self-reported measures, BCI - EEG offers more objective (less subjective) and impartial measurement of social, cognitive, emotional, and decision-making processes. BCI interfaces are becoming more affordable and accessible; IS researchers can benefit by triangulating their existing data sources with brain data. Brain data can also be used specifically for recording and gauging processes related to mental ability that people are not able to self-report accurately (Pavlou et al., 2007). IS researchers can overcome the susceptibility of biases in self-reported data by supplementing the data with those collected through brain imaging techniques.

In NeuroIS, research attempts have been made to use theories and tools in cognitive neuroscience. Moor et al. (2005) and Randolph et al. (2006) used EEG to understand the interaction patterns of the brains of handicapped patients. Differences in the brain activity among men and women during their interaction with recommendation agents were found by Dimoka et al. (2009). Finally, Dimoka (2010) used fMRI and found that trust and distrust cover different areas of the brain. Microsoft utilizes EEG for classifying tasks and recognizing distinctive activities (blogs.zdnet.com/BTL/?p =6609). Applications of NeuroIS in the field of HCI and Design Sciences include: localizing neural correlates associated with usability, capturing hidden processes, complementing existing data sources, and enhancing theories related to design science and HCI (Pavlou et al., 2007).

EEG is considered as BCI's non-invasive neuro imaging technology and measures the postsynaptic electrical potentials on the surface of the scalp (Asadi-Pooya et al., 2017). The activation of neurons leads to synaptic excitations which generate current between dendrites; EEG signals are generated due to such current flows in the cerebral cortex (Sanei & Chambers, 2007). This current generates both electric and magnetic fields; the electric field is measured by EEG and the magnetic field is measured by electromyogram (EMG) (Asadi-Pooya et al., 2017; Salinas & Sejnowski, 2001). Electrodes are positioned at specified locations of the scalp to collect the aggregated synchronized activity from the respective neurons present near the cortex surface. EEG signals are recorded for a short time i.e., typically 20-40 minutes (Taywade & Raut, 2014); these signals are sensitive to noise and they need to be amplified and processed by applying filters and differential amplifiers (Atwood & MacKay, 1989). According to the Nyquist criteria, 200 samples per second (minimum) are required with an effective bandwidth of 100 Hz for the signal amplification. The conventional arrangement of electrodes recommended by the International Federation of Society for Electroencephalography and Clinical Neurophysiology is called 10-20 or 10-10 (Jasper, 1958).

EEG signals can be visually inspected to identify the neurological disorders using brain rhythm patterns. The amplitude and frequency values of these signals vary with human sleep or awaken states, age, health, gender, etc. The five major brain rhythms and their frequency ranges are: delta: 1-4 Hz, theta: 4-8 Hz, alpha: 8-12 Hz, beta 12-30 Hz, and gamma: >30 Hz (Klimesch, 1999). Delta and theta waves are considered low frequency bands; delta oscillations are active during the sleep state (Merica & Gaillard, 1992) and theta oscillations represent cognitive or memory load (Berta et al., 2013; Müller-Putz et al., 2015). Changes in theta activity are related to memory processes, emotional arousal, and impulsivity (Knyazev, 2007). Alpha oscillations are considered medium frequency bands and are active during the awaken state; these oscillations can also be observed when a person closes his/her eyes (Knyazev, 2007). Beta oscillations occur mainly in the frontal and central regions; it is usually associated with focused attention (Berta et al., 2013; Taywade & Raut, 2014). Gamma waves are considered as fast beta waves and have a frequency of above 30 Hz. Detection of these rhythms can be used to identify specific neurological diseases (Pfurtscheller et al., 1994; Taywade & Raut, 2014).

2.5. EEG FOR HCI AND GAMES

An upswing in the brain imaging technologies and cognitive neuroscience increased human ability to interface directly with brain activity (Hjelm and Browall, 2000). In the medical domain, researchers applied BCI to benefit disabled users; examples of applications include bio-feedback therapy for treating neurological disorders and prosthesis control (Coyle et al., 2003). Presently, application of EEG in HCI assumes that instruments to gauge the brain activity patterns for normal users are non-invasive. BCI-EEG applications aim to control game (system) environment in addition to measurement of physical and mental abilities (Nijholt, 2008). Having access to the user's state is valuable to HCI researchers as it opens several other areas of application as discussed below.

Attention Monitoring and Adaptation: It is critical for truck drivers, flight controllers and security personnel to stay awake and alert for longer periods of time; detecting visual alertness becomes a significant prerequisite to monitor user performance (Nijholt et al., 2007). EEG experiments have shown that alpha oscillations are detectors of ongoing brain activity related to awareness and visual alertness (Ergenoglu et al., 2004). These findings provide support in creating BCI applications to determine a user's visual alertness; for example, if a user is not alert, it is possible to adjust the visual load in the interface or advise the user to take a break (Treder et al., 2011). Such systems can be installed at security inspection units, airport traffic control stations etc. to enhance system functionality. The usage of brain activity in combination with other physiological measures is considered as an important multi-dimensional challenge in HCI (Nijholt et al., 2008).

Examples of BCI - EEG applications are as follows:

Controlling systems by affective states: EEG research helps to measure the cognitive activity during specific task scenarios and can analyze and inform users' cognitive states (Ayaz et al., 2011). EEG headsets can be used to segregate the brain activity and these segregations can be used to control the game environment (Chanel et al., 2008). For example, brain activity related to imagining the left foot movement or index finger movement has led to discernible brain activity patterns (Gilleade et al., 2005; Afergan et al., 2014), particularly in the motor cortex regions. A natural mapping of the brain is recorded while users think about carrying out these movements, and this mapping can be used as commands in a game environment, or to operate a prosthetic device or robot. EEG research facilitates the development of applications that derive information from brain activity and control a movement execution.

Evaluating Interfaces and Systems: BCI technologies help to provide optimal and a pleasant user experience by evaluating current systems and interfaces (Coyle et al., 2003). EEG is one of such BCI technologies that can determine specific user states and help to evaluate interfaces or workload systems (Bersak et al., 2001). EEG can be configured to detect errors that the user makes, and to grade and better user performance; for example, based on users' cognitive states, interfaces can be designed more flexibly to manage interruptions (Nijholt et al., 2008). A system can detect deep thoughts or no thought based on the cognitive activity and external cues; if a user is in deep thoughts, then the system manages (delays) interruptions like emails and phone calls. Sensing higher level cognitive states like apathy, boredom, sadness, confusion, flow, anxiety or frustration, happiness, satisfaction and realization (the "aha" moment) helps researchers to build tailored interfaces; such interfaces not only provide feedback but also enhance task focus and strategy usage (Nijholt & Tan, 2007). Finally, developing interfaces based on EEG technology could lead to a remarkable increase in information understanding and retention (Nijholt et al., 2008).

Build adaptive interfaces: EEG systems can equip researchers with information related to users' cognitive and attentional states using brain imaging (Nijholt et al., 2008). Such information allows games to be designed in such a way that they not only adapt dynamically to the user's skill level, but also can decrease or increase the task load based on the user's cognitive state or activity (Hirshfield et al., 2009). In a game environment, apart from brain activity, behavioral responses can also be gauged through facial expressions, eye gaze, body movements and physiological responses through skin conductivity, heart rate, and blood pressure. Moreover, measuring brain activity helps to dynamically tailor the games to the affective state of the user, allowing the application to adjust the flow of information and to provide effective and pleasant feedback, thus keeping the user in the flow state while gaming (Gilleade et al., 2005; Afergan et al., 2014). EEG can be used to design interfaces that adapt automatically depending on the cognitive state of the user.

2.6. NEURAL CORRELATES OF USER EXPERIENCE STATES

Neural correlates can be defined as the brain activity or mapping that corresponds to specific states or desired user experience in the context of this research. According to previous studies, cortical activations vary, and these variations can be attributed to changes in task difficulty and attentional demand levels; neural correlates can be used to determine the variations and also to classify the user states of experience (Ewing et al., 2016; Berta et al., 2013). In this section, underlying brain activation patterns for user states such as flow, boredom, and anxiety, are reviewed.

2.6.1. Neural Correlates of Flow-Related User Experience. As reviewed in the previous sections, researchers have modeled and assessed flow somewhat differently in the IS literature. There has been continuing effort by researchers to develop a generalized and robust measurement scale for flow. Recent studies have utilized psychophysiological techniques such as EEG and Magnetic Resonance Imaging (MRI)/Functional Magnetic

Resonance Imaging (fMRI) to analyze neural correlates of user experience, such as flow, by examining the brain activation patterns while performing a cognitive task.

Table 2.3 summarizes empirical research that has investigated the neural correlates of flow state of user experience using EEG or MRI/fMRI. Although the literature has examined the use of EEG for modeling related constructs such as task engagement and workload, there are only a handful of studies that have examined EEG for modeling flow as an optimal state of user experience (Berta et al., 2013; Léger et al., 2014; Wang & Hsu, 2014).

Table 2.3. Summary of Research on Neural Correlates of the Flow State

Reference	Research Setting	Summary of Findings
Bavelier, Achtman, Mani, & Föcker (2012)	Use fMRI to study neural bases of selective attention in video game players	This study used brain imaging to compare attentional network recruitment and distractor processing in action gamers versus non-gamers. A fronto-parietal network of areas showed greater recruitment as attentional demands increased in non-gamers.
Berka, Levendowski, Lumicao, Yau, Davis, Zivkovic, & Craven (2007)	EEG correlates of task engagement and mental workload during performance of cognitive tests	EEG measures are correlated with both subjective and objective scores of task difficulty levels.

Table 2.3. Summary of Research on Neural Correlates of the Flow State (cont.)

Berta, Bellotti, De Gloria, Pranantha, & Schatten (2013)	Use of a 4-electrode EEG to assess flow in games	The most informative bands for discriminating between boredom, flow, and anxiety user states are around low beta, while simple signals from the peripheral nervous system add marginal information.
De Manzano, Theorell, Harmat, & Ullén (2010)	Used EDA and EMG to understand the physiology of flow experience	High flow values associated with activation of zygomati-cus major (ZM, smiling muscle) and sympathetic activation. Flow is also associated with deep breathing. Found no relation between corrugators supercilli (CS, frowning muscle) and flow.
Dietrich (2004)	Neurophysiological theory of flow experience; Theory of hypofrontality	Flow results from down-regulation of prefrontal activity in the brain. During flow state, the activities are performed without interference of conscious control system, making the process efficient and fast.
Goldberg, Harel, & Malach (2006)	Used fMRI to understand the brain activity during flow state	Activity decreases in Medial Prefrontal Cortex (mPFC) during flow state. mPFC contributes to self-referential mental activity. Since flow is a highly focused state of task engagement leading to shut down of self-referential activities, it causes a decrease in mPFC.
Gusnard, Akbudak, Shulman, & Raichle (2001)	Used fMRI to assess neural correlates of the flow state	In the state of flow, the Dorsomedial Prefrontal Cortex (DPC) is expected to have very minimal or no activity. DPC deals with self-related emotions and in the flow state, self-related emotions are eliminated.

Table 2.3. Summary of Research on Neural Correlates of the Flow State (cont.)

Hamilton, Haier, & Buchsbaum (1984)	Used EEG and IES (Intrinsic Enjoyment Scale) to assess the physiological correlates of flow experience	Flow as a personality trait in daily activities. Subjects scored high on IES: the increased attention led to decreased effort measured using EEG, EP (Evoked Potentials).
Keller, Bless, Blomann, & Kleinböhl (2011)	Used ECG/EKG (Electrocardiogram) and Kubios HRV analysis to understand the flow state physiology	Flow experience is associated with elevated cortisol levels, reduced heart rate variability, a stressful state of increased workload. All of the above lead to questioning the current, exclusively positive, picture of the flow phenomenon.
Kivikangas (2006)	Used EEG and EMG (Electromyogram), and Flow State Scale (36 items) to assess physiology of flow experience	Flow is associated with in-creased positive valence and decreased negative valence. Flow is negatively associated with corrugators supercilli (CS, frowning muscle) and found no effect on zygomaticus major (ZM, smiling muscle) and orbicularis oculi (OO, “eyelid muscles”). Increased electrodermal activity (high arousal indication) with an experimental flow condition.
Klasen, Weber, Kircher, Mathiak, & Mathiak (2011)	fMRI correlates of flow experience during video game playing	Flow can be characterized by specific neural activation patterns and functional brain imaging can be used to validate factors of flow.
Léger, Davis, Cronan, & Perret (2014)	Use EEG to analyze neural correlates of cognitive absorption in IT end-user training	Five neurophysiological measures including alpha, beta, electrodermal activity (EDA), heart rate, and heart rate explain a significant portion of variation in cognitive absorption.

Table 2.3. Summary of Research on Neural Correlates of the Flow State (cont.)

Li, Jiang, Tan, & Wei (2014)	Use EEG to quantify the cognitive activities of user-game engagement	Different levels of EEG theta oscillations were observed when individuals played games of different levels of familiarity and complexity.
Mandryk & Atkins (2007)	Used EDA (Electrodermal Activity) to assess the skin conductance during flow state	EDA can be used to assess flow, which is associated with emotional arousal.
Nacke & Lindsey (2009)	Used EDA and EMG to understand the physiology of flow experience	Increased activity of zygo-maticus major (ZM, smiling muscle) and orbicularis oculi (OO, "eyelid muscles") and an increase in electrodermal activity (EDA) is associated with the experimentally induced flow condition.
Peifer (2012)	Used Questionnaire and Electrocardiography (ECG/EKG) to understand the physiological correlates of flow experience	Flow has an inverted u-shaped relation with hypo-thalamic-pituitary-adrenal (HPA) axis activation and sympathetic arousal.
Pope, Bogart, & Bartolome (1995)	Select indices of operator engagement in automated task based on EEG signals	The index that is made up of the formula: beta power/(alpha power + theta power) reflects operator engagement.
Sanchez-Vives & Slater (2005)	Used fMRI to assess neural correlates of flow state in virtual reality	Modern video games evoke strong feelings. The sensory motor network is activated during the flow state. Flow influences midbrain reward structures.
Wang & Hsu (2014)	Understand flow experience in a computer-based instruction environment using EEG	Learners with high flow experience show high-ranking learning performance. Attention percentages are high during the flow state.

So, what happens in the human brain during the flow state? Using an experimental study, Berta et al. (2013) found that the most informative frequency bands for differentiating between flow, boredom, and anxiety include those around the low beta band. Léger et al. (2014) found cognitive absorption to be positively related to EEG alpha and negatively related to EEG beta. On the other hand, Pope et al. (1995) devised an index for task engagement as beta power divided by the addition of alpha and theta power. Given that task engagement and cognitive absorption are closely related constructs, the findings by Léger et al. (2014) and Pope et al. (1995) are seemingly inconsistent and in the opposite direction. In this research, we hope to further investigate the relationships between the frequency bands and the flow state to help in resolving this inconsistency. Li et al. (2014) found that the density of theta oscillations from the left side of the dorsolateral prefrontal cortex can explain user engagement. Berka et al. (2007) found that task engagement, which is a concept closely related to flow, correlates with EEG activity in the theta, alpha, and beta bands.

2.6.2. Neural Correlates of Boredom-Related User Experience. Research studies have utilized neuroimaging technique (fMRI) to measure the neural correlates of the boredom state. These studies reported that, during boredom, the frontal, and temporal lobes were consistently active whereas the other regions of the brain were less active (Ulrich et al., 2014; Mathiak et al., 2013; Andrews-Hanna, 2012; Buckner et al., 2008); during active task engagement, the activity in the frontal and temporal regions was seen to be reduced (Gusnard & Raichle, 2001).

Indeed, it has been found that when a person is actively engaged in a cognitively demanding task, activity in the frontal and temporal regions is low when compared to the central executive network (Mason et al., 2007; Danckert & Merrifield, 2016). Table 2.4 summarizes empirical research that has investigated the neural correlates of boredom state using EEG or MRI/fMRI.

Both EEG and fMRI studies reported a link between the boredom experience and neuronal oscillations. Oswald (1962) was the first researcher to suggest the possibility of the existence of neurophysiological markers for the state of boredom. He also hypothesized that an increase in the alpha band activity may be linked to both boredom and visual inattention (Oswald, 1962). This hypothesis turned out to be consistent with later studies conducted on the alpha waves by Gevins and Schaffer's (1979) who found that cortical activation related to a task is inversely proportional to the magnitude of alpha waves, and by Klimesch (1999) who found that alpha oscillations are active during mental inactivity and wakeful relaxation.

Table 2.4. Research on Neural Correlates of the Boredom State

Reference	Research Setting	Summary of Findings
Danckert & Merrifield (2016)	Used fMRI to study the boredom, sustained attention, and DMN (Default Mode Network)	DMN is active during boredom. Activated regions of DMN included lateral temporal cortex, medial Prefrontal cortex (mPFC), posterior cingulate cortex, and precuneus.
Kramer (2007)	Used EEG and GSR to predict performance	A negative correlation between theta and mid-beta activity with performance. Decrease in alpha over temporal region leads to better performance.

Table 2.4. Research on Neural Correlates of the Boredom State (cont.)

Mathiak, Klasen, Zvyagintsev, Weber, & Mathiak (2013)	Used fMRI to understand user experience states while playing a video game	Boredom has been operationalized as a passive state with a negative effect. Boredom was associated with activation of the ventromedial Pre-Frontal Cortex (vmPFC) and insula. In addition, right precuneus and hippocampus were deactivated during boredom.
Ulrich, Keller, Hoenig, Waller, & Grön (2014)	Used fMRI to study neural bases of flow with boredom and anxiety as comparison conditions while performing an arithmetic task	Medial prefrontal and temporal cortex are highly active during boredom in comparison with flow. Left amygdala, hippocampus, and parahippocampus gyrus were also highly active during boredom when compared to flow.

According to the findings related to fMRI and EEG neuronal oscillations, EEG's theta, alpha, and beta (mid-beta) activity over the frontal and temporal regions of the brain can be used for analyzing the neural correlates of the boredom state.

2.6.3. Neural Correlates of Anxiety-Related User Experience. Dornic (1977) conducted a self-reported study and asked participants about their invested efforts to complete the task. The results show that highly anxious individuals spent more effort when compared to less anxious individuals. This result is in line with Dronic's next study, where it was found that anxiety can increase mental load, causing no harm to performance (Dornic, 1977, 1980). Another way to measure the expended effort during the state of anxiety is through physiological measures. A group of highly anxious people showed more cardio vascular activity when compared to less anxious people (Schwerdtfeger & Kohlmann, 2004).

However, no significant difference was found between highly anxious and less anxious groups in the cardiovascular indices that signify effort during task performance (Calvo et al., 1996; Di Bartolo et al., 1997; Scho¨npflug, 1992). Physiological studies suggest that highly anxious people do not put in more effort in cognitive task performance when compared to the less anxious group. As a further step, researchers adopted brain imaging techniques like fMRI and EEG to understand the neural correlates of anxiety in healthy adults rather than focusing on analyzing clinical anxiety. Table 2.5 summarizes the neural correlates of the anxiety state based on the fMRI and EEG studies in the literature.

Table 2.5. Research on Neural Correlates of the Anxiety State

Reference	Research Setting	Summary of Findings
Aftanas & Golosheikin (2003)	Used EEG to identify the cortical activity changes in the alerted states	The Frontal Midline Theta (FMθ) activity correlates negatively with the intensity of the anxiety experienced.
Ansari & Derakshan (2011)	Used fMRI techniques to analyze the neural correlates of inhibited anxiety	Fronto-central regions of the brain are inhibited during high anxiety levels and highly anxious individuals showed lower ERP (Event Related Potentials) activity. Anxiety is associated with reduced recruitment of prefrontal attentional mechanisms.
Berta, Bellotti, de Gloria, Pranantha, & Schatten (2013)	Used EEG to assess the physiological correlates of flow with anxiety as a comparison condition	EEG theta activity is low during the state of anxiety or frustration when compared to boredom and flow states

Table 2.5. Research on Neural Correlates of the Anxiety State (cont.)

Birbaumer (1977)	Used EEG to monitor theta changes during anxiety and after meditation	EEG theta activity is low during state of anxiety and increased after meditation
Dolcos, Iordan , & Dolcos (2011)	Used fMRI to investigate the neural correlates of emotion – cognition	Dorsolateral Pre-Frontal Cortex (DLPFC) and Dorsomedial Pre-Frontal Cortex (DMPFC) are negatively associated with anxiety scores.
Gillath, Dolcos, Shaver, Wendelken, & Mikulincer (2005)	Used fMRI to explore the neural correlates of ability to suppress negative thoughts	Anxiety negatively correlates with orbitofrontal cortex and is positively associated with hippocampus.
Gruzelier (2009)	Used EEG to understand the theta/alpha neuro feedback	Increase in the theta-alpha ratio reduces the depression and anxiety levels in an individual.
Isotani, Tanaka, Lehmann, Pascual-Marqui, Kochi, Saito, & Sasada (2001)	Used EEG for recording brain activity during anxiety and relaxation	EEG sources were located more towards the right region during anxiety than during relaxation Mid-beta band showed more activation in the frontal lobe during anxiety compared to relaxation.
Knyazev, Savostyanov, & Levin (2004)	Used EEG to understand the alpha oscillations during anxiety	Alpha power increased during low-anxiety level but not during high anxiety.
Liotti, Levin, Brannan, McGinnis, McGinnis, and, Fox (2000)	Used fMRI to assess the cortical correlates of sadness and anxiety	Anxiety is associated with deactivations in the right temporal cortex. The deactivation in the dorsal prefrontal cortex is specific to sadness.
Messina, Sambin, Sambin, & Viviani (2013)	Used fMRI to evaluate the neural correlates of anxiety and depression	Activation in temporal cortex during resting stage and deactivation during the state of anxiety. An increased activation in the Medial Temporal Lobe (MTL) is observed during depression or anxiety

Table 2.5. Research on Neural Correlates of the Anxiety State (cont.)

Mizuki, Kajimura, Kajimura, Suetsugi, Ushijima, & Yamada (1992)	Used EEG to assess frontal midline theta	The Frontal Midline theta (FMθ) was low in a group with high anxiety levels when compared to a group with low anxiety levels.
Putman (2011)	Used EEG delta – beta coherence in relation to anxiety	EEG beta activation is negatively associated with experimentally induced anxiety levels.
Sehlmeyer, Knyazev, Schöning, Kugel, Pyka, Pyka, & Konrad (2011)	Used fMRI to understand the neural correlates of anxiety	Increased activation of amygdala and decreased activation in Pre-Frontal Cortex (PFC) during high levels of trait anxiety have been observed.
Spampinato, Wood, De Simone, & Grafman (2009)	Used fMRI to investigate the neural correlates of anxiety in healthy volunteers	Medial Pre-Frontal Cortex (mPFC) and Dorsolateral Pre-Frontal Cortex (DLPFC) have shown inverse volumetric correlation with anxiety.

Based on the above summarized studies, the literature suggests that the anxiety state can have significant impact on the distributed neural networks of the brain. fMRI studies have shown that a distributed neural network consisting of amygdala, posterior cingulate cortex, and dorsolateral and medial prefrontal cortex have an inverse volumetric relationship with anxiety levels in the healthy group (Spampinato et al., 2009). Further examinations revealed that participants with low grey matter in the temporal lobe tend to have higher levels of anxiety when compared to participants with high gray matter in similar regions (Spampinato et al., 2009). According to fMRI studies, a deactivation in the fronto-parietal network can be observed during intense/high anxiety states. The results of the EEG research studies are in line with the fMRI results. If a task is consistent in nature, the EEG theta decreases even under high load or overload conditions (Axmacher et al., 2008). Although fMRI and EEG results indicate that the brain activity decreases during the anxiety state, a gap in the literature exists (Spampinato et al., 2009). The gap can be explained as follows: least attempts in the literature were made to find the relationship between EEG spectral band activities and the regions of distributed neural network activated/deactivated during the anxiety state.

In summary, our review of the literature suggests that the neural mapping of the flow, boredom, and anxiety states in gaming is unclear and inconsistent in the literature and hence, further research is needed. Among all psychophysiological technologies, EEG is particularly suitable and feasible to analyze brain activity associated with the flow, boredom, and anxiety states in the HCI context because it provides continuous assessments of user states during a user’s interaction with computers or technology.

3. THEORETICAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

In Section 3.1, we review theories that were used to justify the research hypotheses; they include motivational theory, effortless action and attention theory, and theories related to flow. Section 3.2 reviews the spectral bands and their nature of correlations towards user states as reflected in the frontal, parietal, temporal, and occipital regions of the brain by comparing flow with resting, boredom, and anxiety.

3.1. THEORETICAL FOUNDATION

Based on the theories of flow and effortless attention (Bruya, 2010; Csikszentmihalyi, 1975), a user who is in the flow state exhibits a high degree of focused attention and concentration, but does so in an effortless, automatic and spontaneous manner. Under normal circumstances, as the demands for a task increase, a higher level of effort is required to maintain the same level of task efficacy (Kahneman, 1973). However, as illustrated in Figure 3.1, when a user achieves and sustains the flow state, the perceived or felt effort does not increase, and may even decrease, when task demands increase (Bruya, 2010). The subjective effort decreases or remains the same with increased task demands due to a very high level of automaticity, focused immersion, and autotelic experience achieved in the flow state. As long as the user maintains the flow state, the felt effort will decrease or remain low.

In addition to the theories of flow and attention, the Transient Hypofrontality Theory (THT) proposes a mechanism of the neural substrates for altered states of consciousness; this theory is also based on the neuroanatomy of the consciousness and is also composed of self-referential processing which is an attribute of the consciousness. The changes in the levels of consciousness have been localized in the prefrontal cortex. Because prefrontal cortex exists as one of the topmost layers of the cerebrum, any changes to the conscious experience should affect first and foremost in this structure of the brain (Ashby & Casale, 2002; Dienes & Perner, 1999).

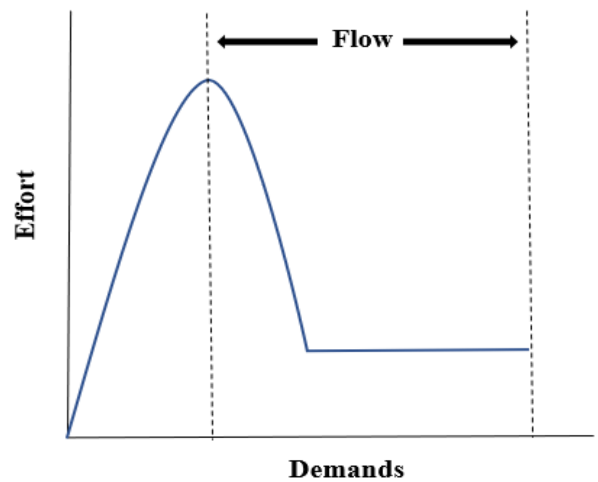


Figure 3.1. Effort vs. Demands in Effective Action in the Flow State, adapted from Bruya (2010)

The neural mechanisms related to the downregulation of the mental activity is directly associated with the altered levels of the referential processing. The progressive shut down of the prefrontal hypoactivity contribute to the decrease in the self-reflection or self-referential processing. During the flow state, the mental functions computed at the level of the prefrontal cortex tend to decrease followed by a gradual decrease in the consciousness (self-reflection) (Dietrich & Stoll, 2010). The ability to process oneself from the surroundings decreases with a decrease in the mental load during high task attentional demands.

To relate theories of flow, effortless attention, and transient hypofrontality to the functions at different regions of the human brain, we first review the functions that are specific to the four lobes of the human brain (see Figure 3.2): frontal, parietal, temporal, and occipital. The frontal, parietal, and temporal lobes are discussed because of their crucial role in cognitive processes. Their functions are provided in Table 3.1.

Table 3.1. Functions of the Lobes of the Human Brain

Human Brain Lobe	Functions
Frontal Lobe	Planning, Motor/Physical movement, Emotion, Problem-solving, Executive process
Parietal Lobe	Perception of stimuli associated with movement and recognition, Selective attentional processes
Temporal Lobe	Memory, Speech, Perception of stimuli, recognition of auditory stimuli
Occipital Lobe	Visual processes

3.1.1. Frontal Lobe. The frontal lobe is functionally related to central executive processes (Sanei & Chambers, 2013). Frontal EEG activities are associated with information processing and stimuli generation for tasks involving cognitive execution process activation (Harmon-Jones, 2003; Jenkins & Brown, 2014); they are also related to automatic processing and rewarding behavior (Stuss & Alexander, 2000; Fuster, 2000).

Thus, the frontal region plays an important role in the flow state because of automatic processing (i.e., arising from merging of awareness and action) of the task and the intrinsically rewarding or autotelic experience.

A large number of studies have shown that the frontal cortex is involved in working memory processing of goal-directed tasks, irrespective of whether the task is related to reasoning, speech, or behavior (Fuster, 2000). The left frontal region of the brain is also related to positive emotional valence and motivation, while the right frontal region of the brain is related to negative emotion and withdrawal motivation (Afergan et al., 2014; Harmon-Jones, 2003; Kalbfleisch & Gillmarten, 2013; Stuss, 2011). Hence, the left frontal lobe corresponds to the most significant region of the brain that relates to autotelic or intrinsically rewarding experience in the flow state.

3.1.2. Parietal Lobe. The parietal cortex functionally supports the memory processes, visual attention and working memory (WM – short term memory) through selective attention-based mechanism (suppresses irrelevant and enhances relevant activities) (Brancucci, 2012; Hill & Schneider, 2006). WM refers to “short-term maintenance and manipulation of items” (Baddeley & Hitch, 1974, p. 45). Interactions between the frontal, temporal, and parietal lobes are considered crucial for various cognitive tasks (Jensen & Lisman, 2005). A growing evidence exists that frontal cortical activation is distributed on the frontal and parietal networks (Kondo et al., 2004; Osaka et al., 2004). In addition, using EEG, researchers found that the fronto-parietal network is involved in the visuospatial working memory (Sauseng et al., 2004). A substantial decrease in the posterior parts of the brain (parietal cortex) occurs once the required skill has been acquired to perform the given cognitive task (Brancucci, 2012; Hill &

Schneider, 2006). Parietal lobes are expected to be less active or inactive during the flow state because of the inhibition of the self-related emotional processing (Gusnard et al., 2001).

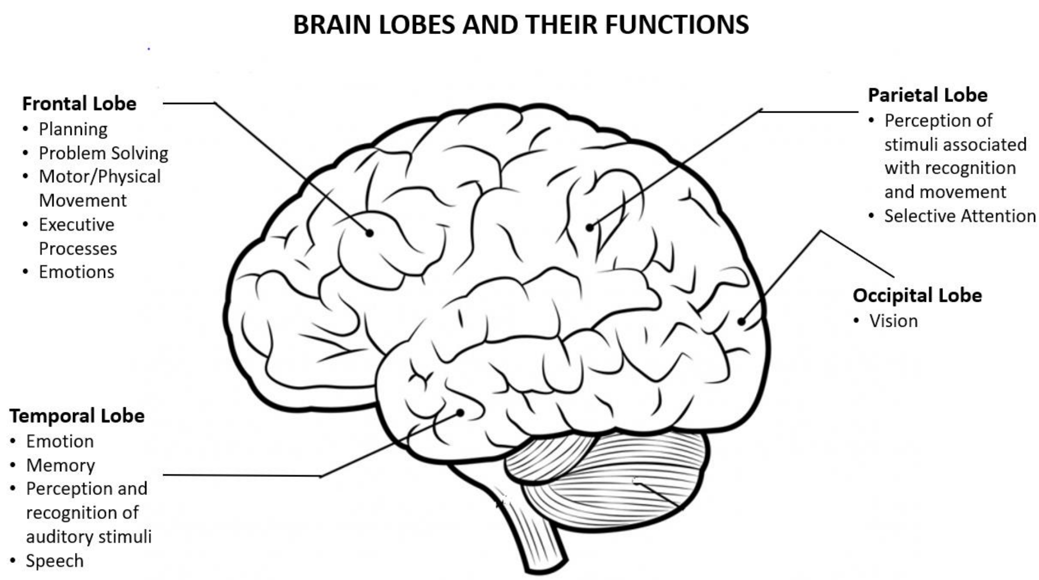


Figure 3.2. Functions of Four Lobes of the Human Brain

3.1.3. Temporal Lobe. The temporal region of the brain is involved in detecting visual and auditory stimuli, processing tactile, and memory storage, suggesting a critical role in the multimodal perceptual analysis (Olson et al., 2007; Hill & Schneider, 2006). Medial Temporal Lobe (MTL) is involved with working memory and can also be considered to measure cognitive load (Kumar & Kumar, 2016). Increase in the task load tends to decrease WM, which in turn leads to a decrease of activity in the frontal and temporal lobes (Axmacher et al., 2008).

Research studies found that with continuous practice of working memory tasks, activity decreases in the frontal, temporal, parietal, and occipital lobes (Axmacher et al., 2008). An increased activity in the temporal region during the first-person shooter game co-related with high planning (highly sensitive to greater complexities). The game moves during temporal activation revealed active processing of information related to the game environment (Montag et al., 2012). Temporal lobes are specialized to perform object processing; these lobes are also activated during scrambling objects (puzzles), scenes, viewing objects, pictures, etc. (temporal lobe is involved in object learning).

Previous studies have found that EEG signal frequencies (such as alpha, beta, and theta bands) correlate with different cognitive states (e.g., Berta et al., 2013; Chanel et al., 2011; Ivanitsky et al., 2009). To better understand the neural correlates of flow, boredom, and anxiety experiences, EEG activities in different regions of the brain need to be converted into spectral band frequencies (see Section 2.4) and examined with respect to individual lobe functions (Brann et al., 2007).

3.2. HYPOTHESIS DEVELOPMENT

With an increase in the game/task difficulty, a change in the cognitive load can be observed. Theta, alpha and mid-beta over frontal, temporal, parietal, and occipital lobes are specifically sensitive to such changes (Ewing et al., 2016). Among all the spectral bands, theta, alpha, and beta (low-beta and mid-beta) are the bands that need to be analyzed for flow, boredom, and anxiety states (Plotnikov et al., 2012).

3.2.1. Flow vs Resting: EEG Theta over Left Frontal Lobe. Theta (4-8 Hz) oscillations are characterized as low-frequency activity and are associated with central executive processes (Berta et al., 2013; Müller-Putz et al., 2015). In specific, changes in the theta activity are related to working memory, memory load, emotional arousal, and impulsivity (Knyazev, 2007; Klimesch & Doppelmayr, 1996). The potential of EEG theta and alpha bands in the in the fronto-parietal network also reflect central executive processes (Sauseng et al., 2005). An increase in theta activity is associated with an increase in cognitive operations (Cunillera et al., 2012; Jenkins and Brown, 2014). A decrease in theta activity can be observed when the performance of a learned task improves, which results in increased familiarity with the task and effortlessness in execution (Knyazev, 2007). As one's engagement with a game increases, there is a decrease in the density of theta oscillations over the frontal lobes (Li et al., 2014). So, we hypothesize that EEG theta activity in the left frontal region of the brain is lower in the flow state when compared to the resting state.

H1: EEG theta activity in the left frontal region of the brain is lower in the flow state than in the resting state.

3.2.2. Flow vs Resting: EEG Theta over Parietal Lobe. The flow state elicits reduced activity in the theta band, which is generally associated with a decrease in the mental workload (Léger et al., 2014). Reduction in the density of theta oscillations from the left side of the fronto-parietal region is associated with flow (de Manzano et al., 2010; Gusnard et al., 2001). Hence, we expect the theta activity in the frontal and parietal lobes to decrease when an individual is experiencing the flow state because automaticity arising from the merging of action and awareness results in felt effortlessness and reduced working memory load. Given that flow is associated with the left frontal-parietal region of the brain and theta activity is associated with cognitive load and working memory, we hypothesize that based on the theories on flow and effortless attention, EEG theta activity in the left frontal and parietal lobes of the brain is lower in the flow state than in a resting state.

H2: EEG theta activity in the left parietal region of the brain is lower in the flow state than in the resting state.

3.2.3. Flow vs Boredom: EEG Theta over Frontal Lobe. Frontal and parietal lobes are expected to be active in the boredom state based on the literature (see section 2.6.2). fMRI studies that focused on understanding the neural bases of the boredom state reveal the occurrence of brain activation over the frontal electrodes (Jiang et al., 2009; Mathiak et al., 2013). EEG theta activity acts as a “generic” index for mental load/effort due to its sensitivity, reliability, and specificity (Ewing et al., 2016). Theta increases with task difficulty and memory load and is low during the boredom state (McMahan et al., 2014). Nacke et al (2011) demonstrated that EEG theta activity is high in the boredom state when compared to other user states of high cognitive load (Nacke et al., 2011). Further, theta activity has been examined over the frontal regions of the brain and found that boredom has higher cortical activation when compared to resting (D'angiulli et al., 2012). In contrast, theta activity is high in boredom when compared to flow and anxiety (Berta et al., 2013). Amplitude of the theta and alpha bands are significantly higher during the boredom state when compared to the flow state. This can be due to the effortless theory of action and attention that has been explained above (see section 3.1). Based on theories of flow and effortlessness, the theta activity in the left frontal region of the brain is lower in the flow state when compared to the boredom state.

H3: EEG theta activity in the left frontal region of the brain is lower in the flow state than in the boredom state.

3.2.4. Flow vs Anxiety: EEG Theta over Frontal-Temporal Network. The interactions between temporal lobes and prefrontal cortex are considered crucial for various cognitive and memory tasks. A decreased activity in the temporal lobes of the brain resembles a decrease in planned executions (Montag et al., 2012). Such a decrease related to EEG theta activity in the temporal region is related to automated response generation. EEG theta activity in the frontal and temporal regions is correlated negatively with high anxiety levels (Mizuki et al., 1992; Nakashima & Sato, 1992). Previous research found that if the task is consistent in nature, then even under high load conditions, the frontal and temporal activities decrease (Axmacher et al., 2008). A significant decrease was found in fronto-temporal regions during a state of anxiety. (Sachs et al., 2004). The activity in the temporal region of the brain decreases further in frustration or anxiety state when compared to resting, boredom, and flow states (Berta et al., 2013). Based on these findings, we hypothesize that the theta activity in the frontal-temporal region of the brain is lower in the anxiety state when compared to the flow state.

H4: EEG theta activity in the frontal-temporal region of the brain is greater in the flow state than in the anxiety state.

3.2.5. Flow vs Resting: EEG Alpha over Frontal Lobe. Alpha (8-12 Hz) oscillations are characterized as medium-frequency activity (Berta et al., 2013); Müller-Putz et al., 2015). These oscillations are associated with arousal, attention, and performance in memory tasks (Klimesch, 1999). The power of the alpha frequency band decreases with increasing task or executive demands that is termed as idling activity; this decrease has been correlated with perceptual success (Sauseng et al., 2005; Kerr et al., 2011; Fink et al., 2005; Ivanitsky et al., 2009); Pfurtscheller and Da Silva, 1999). The alpha activity correlates with relaxation and has an inverse correlation with arousal and attention (Knyazev, 2007). Alpha oscillations support the gating function and are active during the resting state in which people have their eyes closed, and they tend to become inactive when people open their eyes or hear familiar sounds (da Silva, 1991; Horne, 1988; Toscani et al., 2010).

A reduction in alpha activity represents increased attentional activity (Knyazev, 2007; Schier, 2000; Treder et al., 2011). Salinas and Sejnowski (2001) showed that attention can not only lead to a decrease but also can lead to an increase in the firing of neurons. In addition, an increase in the player's focus and concentration is supposed to be reflected in higher attentional demands (Klasen et al., 2011). Alpha synchronized activity can be interpreted as a neurophysiological correlate of decreased cortical activity (Ergenoglu et al., 2004), whereas alpha desynchronization is related to increased cortical activity. Individuals are able to sustain high attention and focused concentration in a spontaneous and effortless manner to achieve an autotelic experience during the flow state. When high attentional focus is sustained in the flow state, alpha desynchronization takes place to produce low theta. Hence, EEG alpha activity in the left frontal region of the brain will be lower in the flow state than in the resting state.

H5: EEG alpha activity in the left frontal region of the brain is lower in the flow state than in the resting state.

3.2.6. Flow vs Boredom: EEG Alpha over Frontal Lobe. Boredom occurs due to a mismatch between skill level and attentional capacity to carry out task requirements

(Berlyne, 1960; Csikszentmihalyi, 1975, 1992). According to the arousal and attentional theories, boredom is related to attentional failure with low level of arousal (Gerritsen et al., 2014; Pattyn et al., 2008; Eastwood et al., 2012). Task-unrelated thoughts are considered to correlate with boredom leading to attentional failure (Danckert & Merrifield, 2016). Boredom is also characterized as a "low arousal affective state" (Mikulas & Vodanovich, 1993). Geiwitz (1966) induced experimental boredom and found its association with low levels of arousal and attention (Geiwitz, 1966). Alpha increases during the state of boredom, meaning that attention is decreased (Tabatabaie et al., 2014). Alpha is high in the boredom state when compared to the flow state in the frontal region of the brain (Labonté-LeMoyne et al., 2016)]. Frontal alpha is high when demands are low but low when demands are high and excessive (Ewing et al., (2016). Alpha activity is high in boredom when compared to flow and anxiety (Berta et al., 2013). The manipulation of game demands is also sensitive over temporal and frontal regions of the brain (Ewing et al., 2016). So, we hypothesize that alpha activity in the left frontal region of the brain is lower in the flow state when compared to the boredom state.

H6: EEG alpha activity in the left frontal region of the brain is lower in the flow state than in the boredom state.

3.2.7. Flow vs Resting: EEG Mid-Beta over Frontal Lobe. Beta (12-30 Hz) oscillations are characterized as high-frequency activity (Bekisz and Wróbel, 1999; Jenkins and Brown, 2014). Beta refers to the active attention state, often referred as alertness, and it increases with processing demands (Dietrich and Stoll, 2010; Horne, 1988; Marr, 2001). Researchers found that dorsomedial prefrontal cortex (DLPFC) is associated with emotional processing related to oneself (own) and beta oscillations represent such self-referential processes (cognitive processes associated with relating/processing information to oneself) (Gusnard et al., 2001; Ergenoglu et al., 2004). The beta band is usually considered the longest band due to its frequency range, i.e., 12-30 Hz. Berta et al (2013) divided beta band into three sub-bands: low-beta (12-15 Hz), mid-beta (15-20 Hz), and high-beta (20-30 Hz) to perform more refined analysis on user states of experience (Berta el al., 2013).

Mid-Beta desynchronization reflects a change in event-related information processing and performance (Klasen et al., 2011; Kramer, 2007), while synchronization is related with an altered existing cortical network (Klimesch, 1999). Mid-Beta activity decreases during sensory and information processing and this decreased activity supports the loss of alertness (Ergenoglu et al., 2004; Kramer, 2007). An increase in the beta activity is associated with a high level of vigilance in the task (Hartmann and Klimmt, 2006) and cortical activation is accompanied by an increase in beta frequency activity (Barry et al., 2007; Bavelier et al., 2012; Dietrich & Stoll, 2010). In addition, mid-beta has been linked to the state of alertness and self-awareness. Mid-Beta occurrence in the left hemisphere has been found to correlate negatively with performance (Kramer, 2007; Berta et al., 2013). Hence, we hypothesize that EEG mid-beta activity in the left frontal region will be lower in the flow state than in the resting state.

H7: EEG mid-beta activity in the left frontal region of the brain is lower in the flow state than in the resting state.

3.2.8. Flow vs Boredom: EEG Mid-Beta over Frontal Lobe. Beta waves are consistently associated with attention and alertness (Tinguely et al., 2006) and increase with a feeling of spatial presence (Nacke, 2010). Mid-Beta in the left hemisphere was found to correlate negatively with performance (Kramer, 2007). A high mid-beta power is expected to be low during the flow state given that it is linked to attentional focus based on the transient theory of the hypofrontality explained under the theoretical foundation (downregulation of self-referential processes during flow state) (Dietrich & Stoll, 2010). A research study conducted by Tabatabaie et al. (2014) found low beta power over the dorsolateral prefrontal cortex (DLPFC) when subjects listened to self-reported boring music (Tabatabaie et al., 2014). Mid-Beta activity is low in the flow state when boredom over the frontal regions (Berta et al., 2013; Dietrich & Stoll, 2010). The states of alertness and self-awareness have also been linked to the mid-beta range (Kramer, 2007) whereas reduced self-awareness is a part of the flow state (Csikszentmihalyi, 1999). An inconsistency exists in understanding the mid-beta activity; we base our discussions and findings on mid-beta's relation to alertness and attentional levels of the game research. So, based on the transient theory of the hypofrontality above findings related to the video games we hypothesize that mid-beta activity in the left frontal region of the brain is lower in the flow state when compared to the boredom state.

H8: EEG mid-beta activity in the left frontal region of the brain is lower in the flow state than in the boredom state.

3.2.9. Flow vs Resting: EEG Alpha over Occipital Lobe. Visual information processing represents a crucial aspect in cognitive performance (Klimesch, 1999). The occipital regions of the human brain record dominant activity of visual attention during application of rigorous visual strategies on a given task (Goldman et al., 2002). The alpha band activity is the most prominent EEG signal recorded in the occipital portion of the brain, representing visual attentional processes (Teplan, 2002). The occipital region has been considered as an index for visual attention and general arousal (Sadato et al., 1998). Alpha desynchronization reflects an activated neuronal population resulting from focused attention (Ergenoglu et al., 2004). Given that the occipital region is associated with visual attention, alpha desynchronization that results from enhanced visual information processing during the flow state produces low theta in the frontal region (Cahn & Polich, 2013; Gerĕ & Jaušcvec, 1999). Todd and Marois (2004) found that an increase in the player's focus is accompanied by deactivation in the frontal cortex and activation in visual areas (occipital lobe). Hence, we hypothesize that EEG alpha activity in the occipital region will be lower in the flow state than in the resting state.

H9: EEG alpha activity in the occipital region of the brain is lower in the flow state than in the resting state.

In summary, we hypothesize that alpha activity in the left frontal and occipital lobes decreases during the state of flow when compared to the resting and boredom states. This phenomenon arises because of focused attention and concentration during the flow state, where alpha desynchronization in the left frontal region is associated with a high level of sustained attentional focus, and alpha desynchronization in the occipital region is associated with the automatic processing of the visual stimuli of the task. The theta activity in the left frontal and parietal lobes also decreases during the flow state when compared to the resting and boredom states because of reduced working memory load or decreased felt effort to process the task when one is in the flow state. The theta activity decreases further over the frontal-temporal region in the anxiety state when compared to the flow state. The mid-beta activity also decreases in the left frontal lobes during the flow state because of deactivation of the self-referential processes. The hypotheses for this research focus on understanding the relationship between theta, alpha, and mid-beta activity over the frontal, temporal, parietal, and occipital regions of the brain. Table 3.2 summarizes the hypotheses.

Table 3.2. Study Hypotheses

EEG Band Activity	Human Brain Lobe	Hypothesis
Theta	Left Frontal	H1: EEG theta activity in the left frontal region of the brain is lower in the flow state than in the resting state.
	Left Parietal	H2: EEG theta activity in the left parietal region of the brain is lower in the flow state than in the resting state.
	Left Frontal	H3: EEG theta activity in the left frontal region of the brain is lower in the flow state than in the boredom state.
	Frontal-Temporal	H4: EEG theta activity in the frontal-temporal region of the brain is greater in the flow state than in the anxiety state.
Alpha	Left Frontal	H5: EEG alpha activity in the left frontal region of the brain is lower in the flow state than in the resting state.
		H6: EEG alpha activity in the left frontal region of the brain is lower in the flow state than in the boredom state.
Mid-Beta		H7: EEG mid-beta activity in the left frontal region of the brain is lower in the flow state than in the resting state.
		H8: EEG mid-beta activity in the left frontal region of the brain is lower in the flow state than in the boredom state.
Alpha	Occipital	H9: EEG alpha activity in the occipital region of the brain is lower in the flow state than in the resting state.

4. RESEARCH METHODOLOGY

In this section, details regarding the experimental design, research procedures, measurement, and pilot tests conducted will be provided.

4.1. EXPERIMENTAL DESIGN

A within-subject experimental design was used to induce specific states of user experience. A within-subject factor is one where the same group of subjects experience all the evoked user states. Since the goal of this study is to assess the flow state of an individual versus the resting, boredom, and anxiety states, it is more appropriate to use within-subject experimental design, so subjects serve as their own control. However, we did not counterbalance the order of the levels of the gameplay, which were used to induce different states of user experience. A study has shown that players are more likely to build their skills, and over time achieve a state of flow. In other words, it is harder to achieve the intended states of user experience by randomizing the task difficulty rather than increasing the difficulty linearly (Nacke & Lindley, 2008). If players are faced with an initial difficulty that surpasses their skill level, the anxiety of the player could make it very unlikely or difficult to achieve a state of flow later (Nacke & Lindley, 2008).

A laboratory experiment was used to induce user experience states by building on the experimental design by Berta et al. (2013) and using EEG technology to capture the brain activity during these states. Berta et al. used a 4-electrode EEG system and a simple battle plane video game for their study, whereas a 64-electrode Cognionics EEG system (http://www.cognionics.com/) was used for the current study. We adapted their design to the context of our study and used the video game, Tetris[1]. After a comprehensive review involving many video games and piloting them, we chose the Tetris game because (1) it has the flexibility to enable us to induce different states of user experience, (2) the gaming environment can be controlled, i.e., the researcher has the flexibility to limit the duration of gameplay, (3) it allows us to select or specify the difficulty level, and (4) it has the ability to induce the flow state. In addition, it is a simple game that most people are familiar with, which helps to reduce the amount of time spent on training in the experiment. We recruited 44 students to participate in this experiment. The study is comprised of three phases: pre-experiment, experiment, and post-experiment.

4.2. RESEARCH PROCEDURE

Pre-Experimental Phase: During the pre-experimental phase, we provided the subjects with training to ensure they have a clear understanding of the rules and controls of the game. We explained the game as well as the various keyboard and mouse operations to them (refer to the Appendix) during the training session. The subjects were then provided with the opportunity to practice playing the game by starting from level 1. Subjects completed one gameplay (i.e., until all blocks in Tetris stacked up fully) before starting the experimental phase.

Experimental Phase: This research study was conducted in a university computer lab. The research procedures are as follows: The subjects were asked to fill out a pre-study questionnaire to capture their orientation towards gaming. We operationalized the

[1] For an introduction of the Tetris game, refer to https://en.wikipedia.org/wiki/Tetris [Accessed on Feb 5, 2018]

resting state as a baseline by having the subject look at a small cross on a blank screen of the same color as the background of the game used in the experiment; subjects were asked to stay calm and relaxed during the resting state, which lasted for 60 seconds. To induce the boredom state (with the least challenge level), subjects were asked to play the first level (Level 1) of the Tetris game with the mouse clicks disabled so that the subject cannot shorten (or shortcut) the wait time for the falling block to reach the base. A three-minute interval of subject's EEG activity was recorded. A self-reported assessment of user experience was carried out using a questionnaire to validate whether the subjects experienced boredom during the three-minute gameplay. To induce the flow state, subjects were asked to play the Tetris game at level 5 without giving them any time limit. From our pilot study, it was found that starting at level 5 is a good way to elicit flow in the game. The game level continued to increase as subjects improved their skills in playing the game. An assessment of user experience was carried out using a self-reported questionnaire to verify whether the subjects experienced flow during the gameplay. To induce the state of anxiety, subjects were asked to play the Tetris game two times at level 15 and two times at level 20 where the challenge level is substantially higher than the subject's skill level. An assessment of user experience was carried out using a self-reported questionnaire to verify whether the subjects experienced anxiety during the gameplay. Figure 4.1 displays the different levels of Tetris to evoke the required states of user experience. At the end of the study, subjects were asked to fill a background questionnaire that included participant demographics (e.g., age, gender, education), and gaming habits (e.g., how often participants play games and the number of hours per week spent playing games).

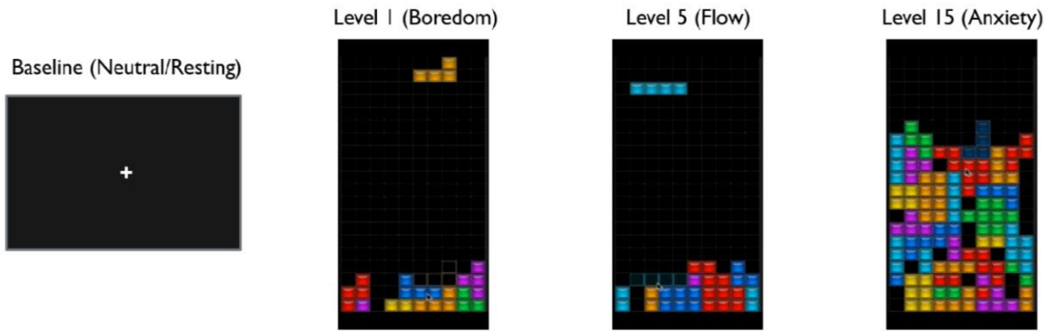


Figure 4.1. Tetris Game at Different Levels to Evoke User Experience States

Post-Experimental Phase: After completing the gameplay, the subjects proceeded to the post-experimental phase to complete a retrospective process tracing that helped researchers to identify the time segments in which subjects were experiencing boredom, flow, and anxiety during the experimental stage. As shown in figure 4.2, during retrospective process tracing, the subjects talked out loud to articulate and verbalize their user experience while viewing a video recording of their gameplay session. The best 30-second segments of boredom, flow, and anxiety experiences were identified and compared with the most stable 30-second segment of the resting condition, which served as a baseline for the data analysis.

4.3. MEASUREMENT

In this study, we used a Cognionics 64- channel dry EEG headset to collect the neurophysiological data while gaming (as shown in Figure 4.3). The recorded EEG has 64 Ag–AgCl pin-type active electrodes mounted in a BioSemi stretch-lycra head cap.

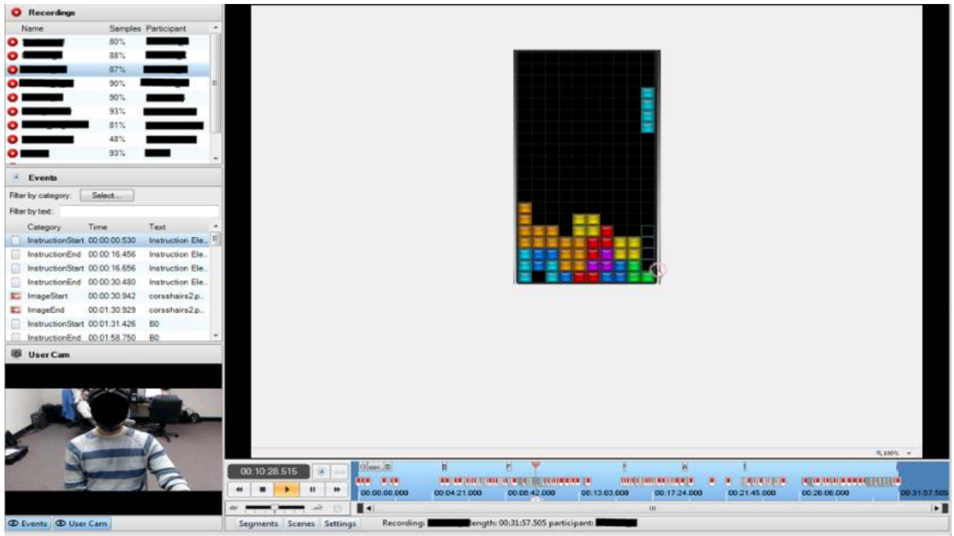


Figure 4.2. Retrospective Process Tracing to Extract a Best 30-Second Segment

Electrodes were positioned using the 10–20 system and recorded activity from the following sites: frontal pole (FPz, FP1 and FP2), anterior-frontal (AFz, AF3, AF4, AF7 and AF8), frontal (Fz, F1, F2, F3, F4, F5, F6, F7 and F8), fronto-central (FCz, FC1, FC2, FC3, FC4, FC5 and FC6), central (Cz, C1, C2, C3, C4, C5 and C6), temporal (FT7, FT8, T7, T8, TP7 and TP8), parieto-central (CPz, CP1, CP2, CP3, CP4, CP5 and CP6), parietal (Pz, P1, P2, P3, P4, P5, P6, P7, P8, P9 and P10), occipito-parietal (POz, PO3, PO4, PO7 and PO8) and occipital (Oz, O1, O2 ad Iz). The data were visually inspected for artifacts (Fairclough et al., 2013). EEG oscillations are recorded as waveforms and are manifestations of the activity of neuronal population of the brain; these oscillations are recorded using flex sensors embedded in the EEG headset (Pizzagalli, 2007). These oscillations represent a subset of the brain's electrical activity at a particular point of time.

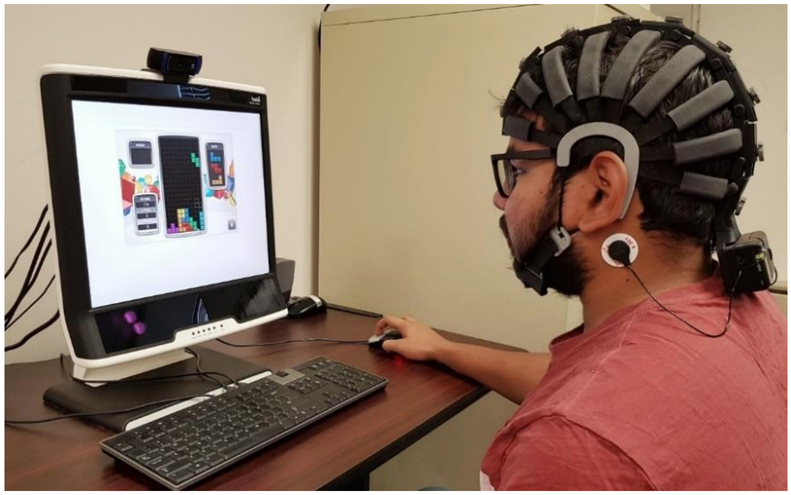


Figure 4.3. A Subject Wearing 64-Channel EEG Device During the Experiment

As shown in Figure 4.4, the device was placed on the subject’s scalp during the experiment, following a 10-20 positioning system (Luu & Ferree, 2005). The “10” and “20” refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% respectively of the total front-back or right-left length of the surface of the skull (Hondrou & Caridakis, 2012). A sampling rate of 512 Hz was used to capture the data for brain activities.

4.4. PILOT TESTS

We conducted five pilot studies to test the following: Browser compatibility with Tetris game website (ad-free), order of stimuli using Tobii Studio, EEG markers using Cognionics software, evoked user states of experience (boredom, flow, and anxiety), survey questionnaire items, randomization of tasks, and experimental procedures.

The first pilot study was used to test and fine-tune the desired game level for evoking boredom, flow, and anxiety user experience states. Results confirmed the generation of boredom state during level 1 and flow state during level 5 but not all subjects experience the anxiety state during level 15 of the gameplay. Among 8 pilot subjects, few claimed to experience flow, and a few of them claimed to experience apathy (disengagement) at level 15. Subjects experienced the flow state because of their proficiency and interest to play Tetris since childhood. Subjects who experienced apathy or disengagement expressed that it is due to a sudden and un-notified change in the challenge level. In order to induce anxiety and control external affecting factors, anxiety level has been redesigned with a combination of level 15 (2 times) and level 20 (2 times). Participants also reported discomfort while reading instructions to navigate from one step to other while performing the study; they felt that navigation instructions were wordy.

The second pilot study was conducted to test the modified design with 8 pilot subjects and the results showed that participants experienced boredom during level 1, flow during level 5, and anxiety during level 15 or 20 or both. Instructions given to participants to move to the next step in the study have been shortened and simplified. It has been identified that participants were willing to receive verbal instructions rather than reading instructions in text form. We had two designs for capturing baseline (resting state): baseline 1 - blank screen with a white background and a black crosshair (size 10) at center, and baseline 2 - blank screen with a black background (matching to Tetris background) and a white crosshair (size 12) at center. Baseline 1 has been tested during the first pilot study and baseline 2 has been tested during the second pilot study. Comparing pilot 1 and pilot 2, results showed that majority of the subjects were more comfortable staring at the white crosshair on a black screen (baseline 2) and claimed to be more relaxed. Browser configurations and compatibility with Tobii studio and an ad-free Tetris game website have also been tested. We found that Internet Explorer does not always succeed in portraying an ad-free Tetris website. So with help of Tobii tech support team, Mozilla Firefox plug-ins were downloaded and configured, and Tetris game website was made completely ad-free and functioned without any flaw.

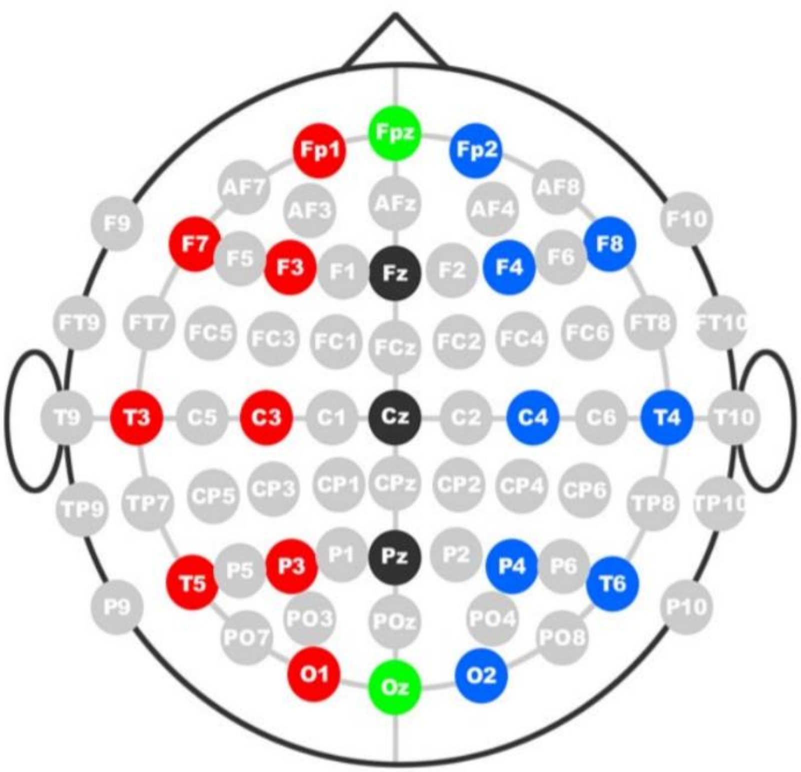


Figure 4.4. EEG Headset 10/20 Positioning System

The third pilot study with 5 subjects was used to test stimuli generation, system configurations, practice EEG markers, and step-by-step process for fixing the EEG headset onto participants' head following the 10-20 international system. In addition, instructions provided during the training stage were bettered and additional information was provided to participants to prevent unexpected pause/resume during the study. Since participants were all male and had experience in gaming, a pre-study questionnaire was added to capture their perception towards gaming. We enhanced the flow related items in the survey questionnaire and added 4 items for validation. Task randomization or counter-balancing was also piloted. Majority of the participants faced discomfort with counter-balancing and were not able to experience a smooth transition from one level to another. Due to these reasons, half of the pilot subjects struggled to build their skills and did not achieve a flow state. For example, a participant who played Tetris at level 15 and 20 experienced anxiety and frustration and claimed that he did not experience boredom and flow during level 1 and 5 due to the intense anxiety that has been experienced at beginning of the study.

The fourth pilot study with 5 participants was used to test the experimental procedures and conditions. When a participant was in the middle of the study, there was a knock on the laboratory door and a participant got deviated from the study and we were forced to pause and redo the study; Warning labels saying “Quiet Zone” to avoid noise and “Experiment in Progress – Please do not Knock” to avoid unexpected visitors/disturbances were designed and put in place. During this pilot test, we also tested the necessity of randomization of the tasks/stimuli. The tasks were not counterbalanced during this pilot study and it was found that all participants experienced their desired states of user experience due to the linear progression of difficulty because players were more likely to build their skills over time and achieved a flow state.

Finally, a fifth pilot study had been conducted to test the stability of all modified and implemented changes related to the software involved, EEG headset, experimental procedures, user experience states, no counterbalancing, and laboratory conditions. Results suggested that all conditions related to the experiment have been standardized, desired user states of experiences were achieved, and no issues with browser and gaming website were found.

5. DATA ANALYSIS AND RESULTS

The sample size for the study is 44 and the duration of the study is approximately 90 minutes. Subjects were both undergraduate and graduate students from Missouri University of Science & Technology. The sample size is calculated using G*Power statistical power analysis (http://www.gpower.hhu.de/). Among the t-tests family, Means statistical test was considered: Difference between two dependent means (matched pairs) and the type of power analysis used is A priori: Compute required sample size – given alpha, power, and effect size. As shown in Figure 5.1, sample size is calculated considering input parameters: tails as one, effect size, f as 0.5, alpha (α) error probability as 0.05, power (1- β (beta) error probability) as 0.90. Thus, our total sample size is calculated as 45. We limited this study to only male subjects in order to control for gender. Participants were recruited through class announcements and email contact.

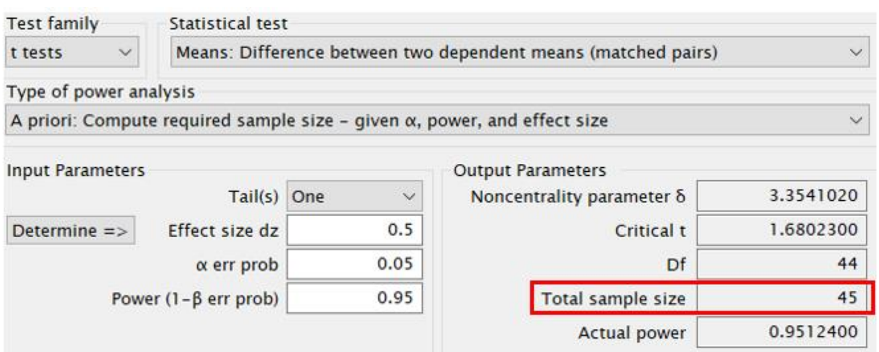


Figure 5.1. Calculating Sample Size Using G*Power Statistical Power Analysis

Paired sample t-test was adopted in this study. Paired sample t-test is a statistical procedure used to determine whether the mean difference between two sets of observations is zero. Each subject or entity is measured twice resulting in pairs of observations. Paired sample t-test is the appropriate technique in this research because this study is within-subject (i.e., comparison of means of brain activity between the flow state and the resting, boredom and anxiety states). All 44 participants were male and were aged between 18 and 30. Pair t-test analysis and validity checks on the user's state of experience were conducted. We used IBM SPSS Statistics 24.0 software to analyze the data collected.

5.1. DATA PROCESSING STEPS

EEG being one of the least invasive BCI technologies holds promise as a neuroimaging technology with excellent neural activity resolution in time domain. (Hairston et al., 2014). It is not possible to record EEG data without any contamination and hence researchers must be careful while considering artifacts in EEG studies. Some limitations of EEG are: (i) lacking spatial resolution, and (ii) cortical electrical activity is extremely small in magnitude when compared to muscle movements across the head. Therefore, participant movements introduce artifacts of high-frequency and magnitude into the EEG data (Minas et al., 2014). Generally, EEG artifacts are classified as biological and non-biological artifacts; major sources of biological artifacts are participants' muscle activities, eye blinks and eye movements, and heartbeat; major sources for non-biological artifacts are primarily external electrical noise, electric lights, computer interference, poor subject grounding, and poor electrode contacts (Harmon-

Jones and Peterson, 2009; Pizzagalli, 2007). As mentioned above, one cannot obtain data that is completely free of artifacts. Thus, measures need to be taken to control experimental environment and detect the artifacts in EEG signals.

5.2. DATA ANALYSIS STEPS

The detailed steps implemented for processing the EEG data are explained below in a stepwise manner. The EEG data obtained from the experimental results have been analyzed using Brain Vision Analyzer (version 2.1).

Changing Sampling Rate: The initial sampling rate while setting up the Cognionics system in experimental stage is 500 Hz. An even frequency resolution can be achieved by having a sampling frequency that is a power of 2, i.e., 512 or 256 Hz instead 500 Hz (Lin et al., 2007). So, to obtain more fine-grained resolution, downsampling (number of samples per second have been decreased) to 256 HZ has been performed applying spline interpolation (see Figure 5.2).

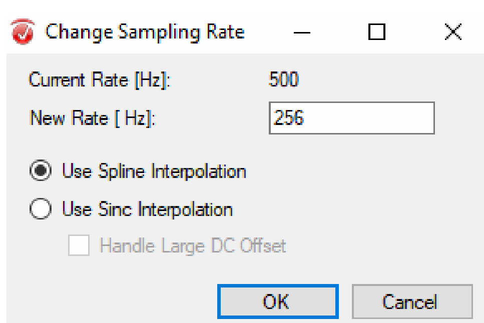


Figure 5.2. Changing Sampling Rate - Downsampling

Optimizing EEG Channel Selection: Generally, multichannel EEG is used in BCI; performing the channel selection enhances the signal processing accuracy by discarding irrelevant channels and promoting relevant channels (Arvaneh et al., 2011). In this study, we have 5 channels which do not contribute to neural activity analysis and these channels are eliminated. Figure 5.3. depicts the channel optimization process. Such customized approach can lead to best signal processing and classification accuracy.

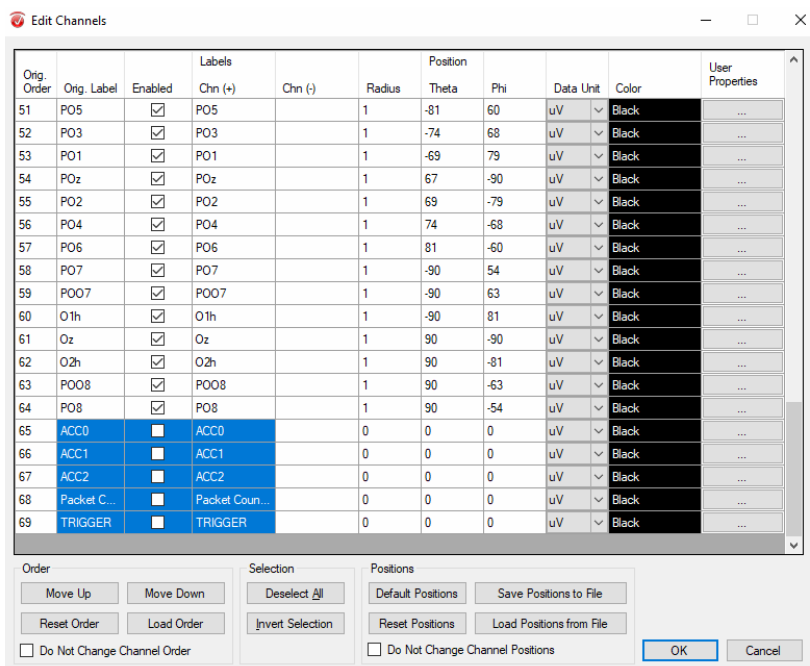


Figure 5.3. Optimizing Channel Selection

Raw Data Inspection/Artifact Rejection: Raw Data Inspection is used for marking artifacts like body movements, environmental noise, eye blinks, and eye movements; it is also sensitive to large offset voltages. These marked data portions are considered as "bad intervals" and are rejected by ocular correction ICA (Independent Component Analysis) based on the rejection criteria (Plank, 2013). As an initial step, an automatic raw data inspection was applied using a built-in algorithm of the Brain Vision Analyzer in a semi-automatic mode at the individual channel level. This algorithm excludes intervals of 200 ms if the voltage of an activity exceeds 50 µV/ms or if it is less than 0.5 µV for a time frame of 100 ms (Figure 5.4 – 5.7) (Ulrich & Hewig, 2014). Implementing this technique in a semi-automatic mode not only helps to discard artifacts but also aids to inspect the data manually (Beste et al., 2015). Figure 5.4 explains the inspection mode as semi-automatic for raw data inspection process. Figure 5.5 and 5.6 provides information related to maximum and minimum voltage criteria. Figure 5.7 is the EEG signal obtained after performing raw data inspection.

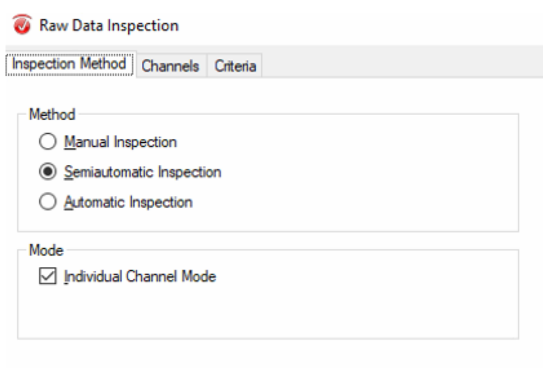


Figure 5.4. Raw Data Inspection: Inspection Mode

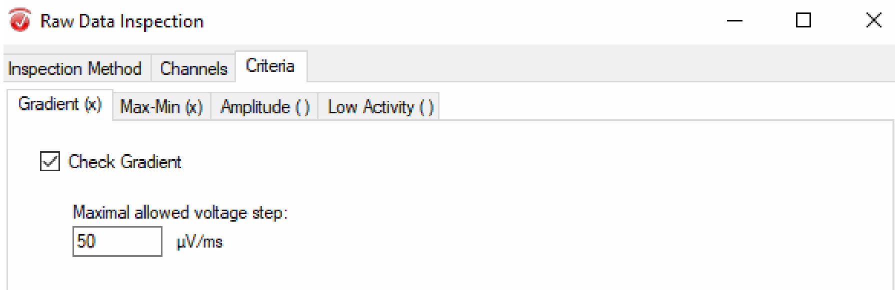


Figure 5.5. Raw Data Inspection: Maximum Voltage Criteria_1

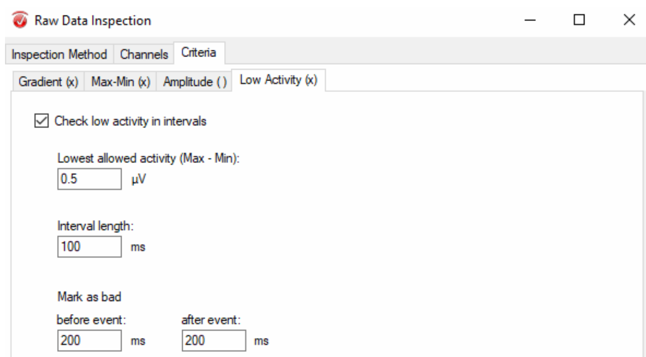


Figure 5.6. Raw Data Inspection: Minimum Voltage Criteria_2

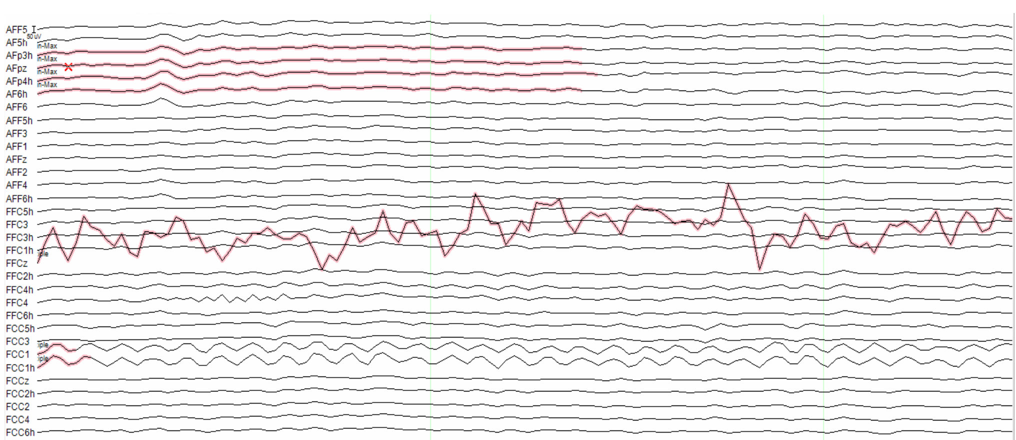


Figure 5.7. EEG Signal After Raw Data Inspection

Ocular Correction ICA: Among the EEG artifacts, ocular or eye movements and eye blinks are considered the most common and notorious artifacts (Minas et al., 2014). These ocular artifacts pose serious problems for interpretation and analysis of EEG signals and can be removed using Ocular Correction ICA.

The regression-based method is the most popular among all Ocular Artifact (OA) removal approaches in the time-frequency domain (Croft & Barry, 2000a; Croft & Barry, 2000b). Regression-based methods can reduce ocular artifacts very effectively if they employ ocular EOG (Electrooculography measuring eye movement) channels (Li et al., 2006). Ocular Correction ICA is not completely dependent on ocular channels (as is, in turn, the regression-based Ocular Correction); the ICA algorithm is not fully reliant on ocular channels and delivers robust components for vertical and horizontal eye movements with scalp channels as well (Plank, 2013). Therefore, in absence of dedicated ocular channels, Brain Vision Analyzer recommends using scalp channels that report respective artifacts adequately. For detecting and rejecting vertical movement (VEOG), AFF5h has been considered as a common reference (see Figure 5.9). Generally, it is recommended to perform Ocular Correction ICA in semi-automatic mode and assess carefully and confirm the selected components as ocular artifacts. Figure 5.8 represents the mode selection for the ocular correction ICA. Figure 5.9 represents the reference channel selection for the and Figure 5.10 represents process of identifying and removing eye-blinks while performing ocular correction ICA.

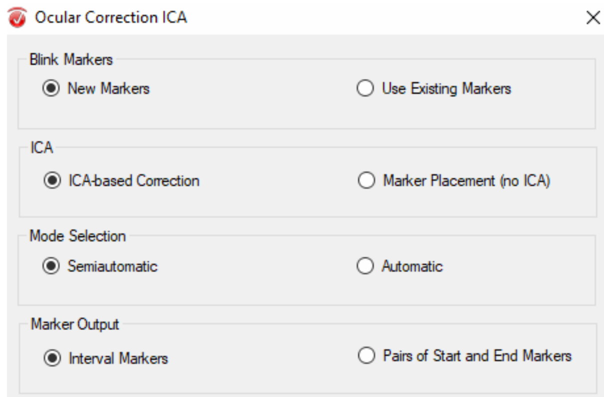


Figure 5.8. Ocular Correction ICA: Mode Selection

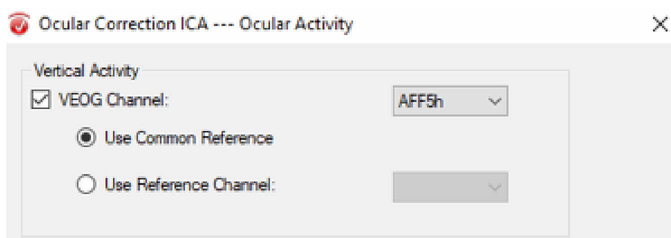


Figure 5.9. Ocular Correction ICA: Reference Channel Selection

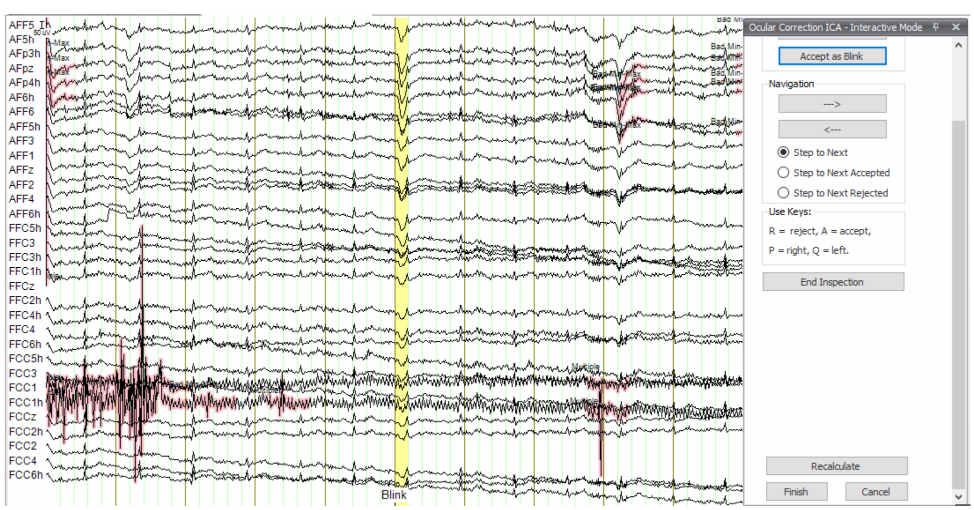


Figure 5.10. Ocular Correction ICA: Identifying and Accepting Eye-Blinks

Filtering: Applying digital filters is considered a common approach to reject EEG epochs containing artifacts with certain pre-selected voltage threshold. However, the amount of data may become unacceptable when muscle movements and blinks occur too frequently in some subjects (Small, 1971; Li and Principe, 2006). To filter the selected voltage, Infinite Impulse Response (IIR) filters are applied (Sanei & Chambers, 2007; Wang et al., 2011) (see Figure 5.11). IIR filters are digital filters used in digital signal processing applications. As shown in Figure 5.11, the recorded EEG signals were analog bandpass filters between 0.1 Hz (Low Pass Filter) and 100 Hz (High Pass Filter); additionally, notch filter was applied at 60 Hz to substantially remove external noise related to line power frequencies.

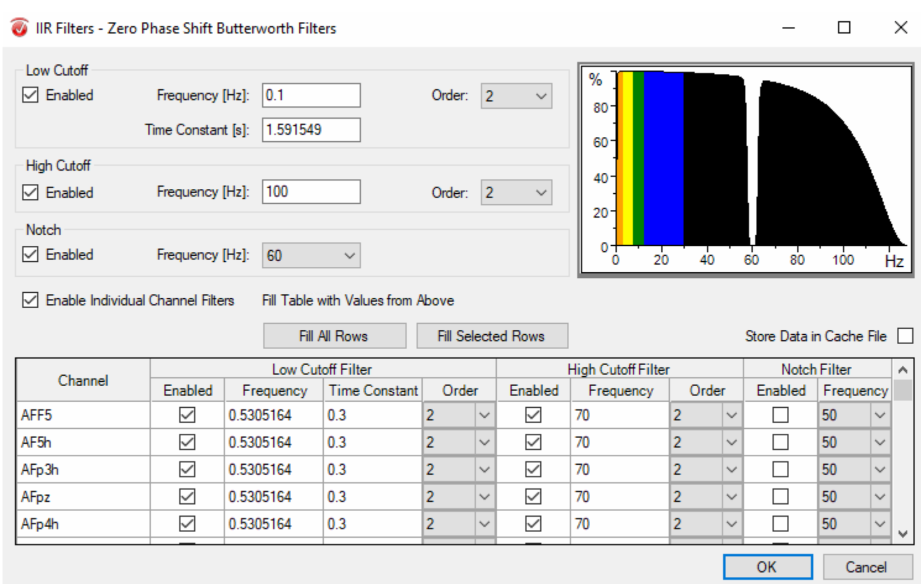


Figure 5.11. Applying Infinite Impulse Response Filters

Segmentation: EEG data can be divided into interval-based epochs to perform further analysis (Bender et al., 2004; Nickel et al., 2006). The processed data is segmented into four divisions based on retrospective process tracing in the experiment stage representing the time frames of experienced user states. As, shown in Figures 5.12 and 5.13, the corrected data has been used to set the newly segmented data manually with respective start and end timestamps (resting, boredom, flow, anxiety); each of the 30 second EEG epochs have been further divided into 100 equal segments and were averaged to obtain enhanced accuracy in results. Figure 5.12 represents the manual division options for segmentation and Figure 5.13 represents the specific timeframes of each user's state.

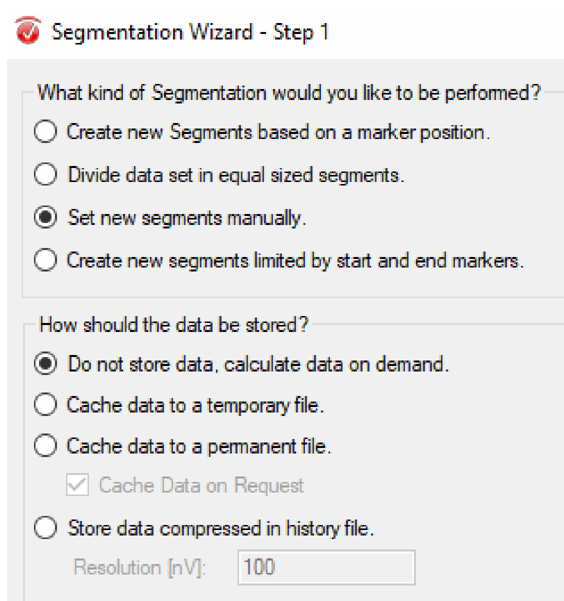
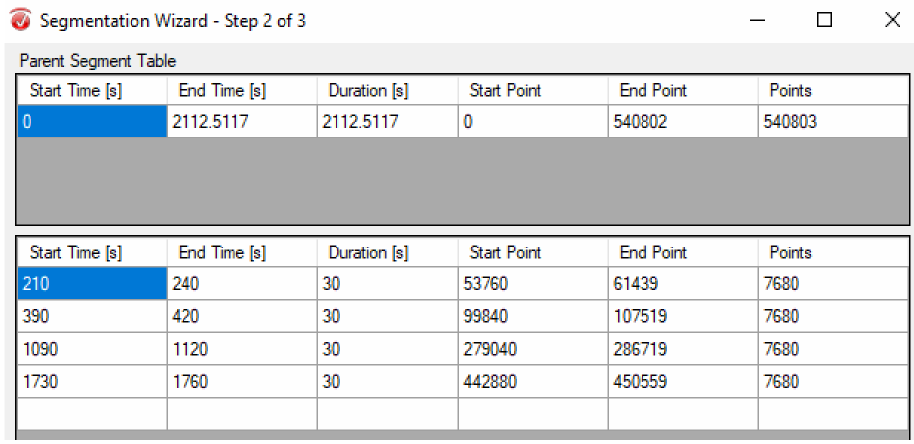


Figure 5.12. EEG Signal Segmentation: Manual Division



Segmentation Wizard - Step 2 of 3

Parent Segment Table

Start Time [s]	End Time [s]	Duration [s]	Start Point	End Point	Points
0	2112.5117	2112.5117	0	540802	540803

Start Time [s]	End Time [s]	Duration [s]	Start Point	End Point	Points
210	240	30	53760	61439	7680
390	420	30	99840	107519	7680
1090	1120	30	279040	286719	7680
1730	1760	30	442880	450559	7680

Figure 5.13. EEG Signal Segmentation: Time Frames of User's States

Fast Fourier Transformation (FFT): The segmented EEG signals are in time-domain (i.e., time on the x-axis); to perform spectral band analysis, these EEG signals need to be converted into frequency-domain (i.e., frequency on x-axis) (Wang et al., 2011). FFT decomposes the time domain signals into frequency domain. By using a built-in algorithm in Brain Vision Analyzer, FFT has been applied to transform the time-domain EEG epochs into equivalent frequency-domain epochs. As shown in figure 5.14, the FFT values of theta, alpha, and mid-beta for resting, boredom, flow, and anxiety were extracted using FFT band export option provided by Brain Vision Analyzer. The mean values of EEG power in different frequency bands (theta, alpha, and mid-beta) and at different brain regions (frontal, temporal, parietal, and occipital) were calculated to identify the neural correlates of the flow state (Kubota et al., 2001). Electrodes in the left frontal region (i.e., AFF1 (F1), AFF3 (F3), and AFF5 (F5)), left parietal region (i.e., CPP1h(P1), CPP3h(P3), CPP5h(P5), CPP7h(P7)), and occipital region (i.e.., O1h(O1), Oz(Oz), O2h(O2)) were pooled to form a cluster. Finally, paired t-tests were performed to assess the hypotheses.

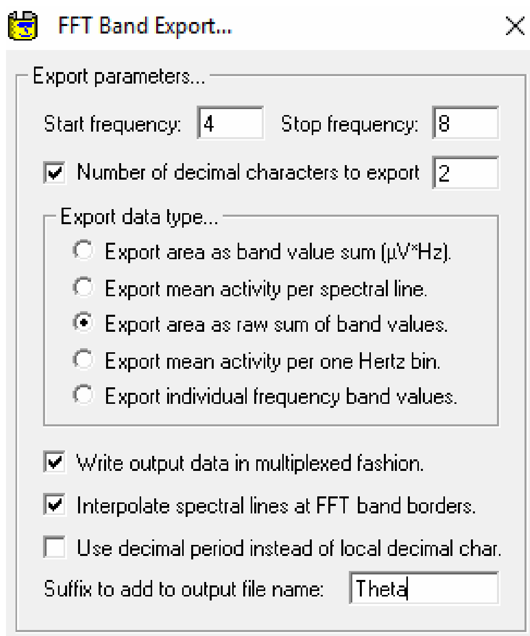


Figure 5.14. Exporting FFT Values for Theta Spectral Band

5.3. RESULTS

Table 5.1 shows the paired *t*-test results that compare the flow, resting (baseline), boredom and anxiety states. The results suggest that EEG power for theta, alpha, and mid-beta in the left frontal region is significantly lower in the flow state when compared to the resting and boredom states ($p<0.05$ for theta, alpha, and mid-beta bands). EEG theta power in the left parietal region is significantly lower in the flow state when compared to the resting state. EEG theta activity in the frontal-temporal region is lower in the anxiety state when compared with flow state. EEG alpha activity in the occipital region is significantly lower in the flow state when compared to the resting state ($p<0.05$). Hence all hypotheses are supported.

Table 5.1. Results of Paired t-tests for Neural Correlates

Hypothesis	Band and Lobe	Experience State	Mean	S.D.	t-value	p-value (1-tail sig.)
H1	Theta - Left Frontal	Flow	8.753	2.627	-2.026	0.02
		Resting	11.95	10.644		
H2	Theta - Left Parietal	Flow	8.456	3.742	-2.217	0.02
		Resting	13.68	15.179		
H3	Theta - Left Frontal	Flow	8.573	2.627	-1.666	0.05
		Boredom	12.482	15.361		
H4	Theta - Frontal-Temporal	Flow	10.338	6.514	1.703	0.05
		Anxiety	8.467	10.185		
H5	Alpha - Left Frontal	Flow	6.31	2.035	-2.181	0.02
		Resting	9.102	8.646		
H6	Alpha - Left Frontal	Flow	6.31	2.035	-2.164	0.02
		Boredom	7.779	5.108		
H7	Mid-Beta - Left Frontal	Flow	4.117	1.217	-1.643	0.05
		Resting	5.858	7.048		
H8		Flow	4.117	1.217	-2.136	0.02
		Boredom	4.7028	2.074		
H9	Alpha – Occipital	Flow	6.212	3.849	-1.743	0.04
		Resting	8.212	7.175		

A secondary analysis has been performed comparing EEG theta, alpha and mid-beta bands potential during boredom and anxiety states with resting state over the left frontal region of the brain. Table 5.2 shows the secondary analysis paired *t*-test results that compare the boredom and anxiety states with the resting (baseline) state. The variation between the boredom and the resting state is not statistically significant during theta, alpha, and mid-beta bands. Anxiety when compared to the resting/baseline is statistically significant in the theta and alpha bands but not during mid-beta band. The change in the levels of the cognitive load and attention can be differentiated between anxiety and resting states when compared to the boredom and resting states.

When a user is in the flow state, there is a decrease in the theta band activity that is associated with a reduction in cognitive load because the theta frequency is associated with working memory and mental load (Knyazev, 2007). As the performance of a learned task improves during the flow state, the theta activity in the left frontal-parietal network decreases, which corresponds to a decrease in the mental workload to carry out the task (De Manzano et al., 2010). A decrease in the theta frequency activity during high task demands is associated with effortless attention (De Manzano et al., 2010). When a user is in the flow state, a decrease in the alpha band activity represents an increase in the task demand (Fink et al., 2005; Ivanitsky et al., 2009). The activity of alpha is inversely correlated with the underlying cortical processes that are associated with arousal and attention (Knyazev, 2007). The observed desynchronization of alpha indicates that users experience effortlessly high attention and high arousal during the flow state to meet high task demands (Knyazev, 2007). Frontal alpha has commonly been associated with mindfulness (Pfurtscheller et al., (2005) and frontal alpha asymmetry has been found to be linked to arousal in gameplay (Davidson et al., 2003).

Table 5.2. Secondary Analysis Results of Paired t-test for Neural Correlates

EEG Band	Human Brain Lobe	Experience State	Mean	S.D.	t-value	p-value (2-tail sig.)
Theta	Left Frontal Lobe	Boredom	12.482	15.361	0.305	0.76
		Resting	11.95	10.644		
		Anxiety	8.495	3.385	-2.157	0.04
		Resting	11.95	10.644		
Alpha		Boredom	7.779	5.108	-1.237	0.22
		Resting	9.102	8.646		
		Anxiety	6.349	2.443	-2.109	0.04
		Resting	9.102	8.646		
Mid-Beta		Boredom	4.702	2.074	-1.151	0.24
		Resting	5.858	7.048		
		Anxiety	4.236	1.463	-1.511	0.12
		Resting	5.858	7.048		

The occipital region of the brain is highly active when performing a cognitive task that requires the implementation of visual strategies (Gerě & Jaušcvec, 1999). Alpha activity and visual attention processes in the occipital region correspond negatively with each other (Ahn et al., 2013; Ergenoglu et al., 2004). Teplan explained that alpha activity heightens in the eyes-closed condition and reduces in the eyes-open condition (Teplan, 2002). A decrement in alpha activity during active states is known as alpha desynchronization. During eyes-closed condition, the visual processing is minimal or absent, whereas eyes-open condition involves a high-level visual processing of the surroundings and tasks, leading to an increase in visual attention and a decrease in alpha activity (Knyazev, 2007; Schier, 2000). When a task involves the application of visual strategies, a decrease in alpha activity in the occipital region of the brain is observed due to visual processes (Gerě & Jaušcvec, 1999). Similarly, alpha activity is decreased in the flow state (as compared to resting and boredom states), because it demands a high level of focus and visual attention for a given task (Barry et al., 2007). According to the theory of effortless attention, during the flow state, a decrease in the alpha frequency of the occipital region and a decrease in the theta frequency of the frontal theta occur without any reduction in user performance (Bruya, 2010).

When a user is in the flow state, a decrease in the mid-beta band activity represents a decrease in active attention with an increase in the task demand (Jenkins and Brown, 2014). The activity of mid-beta is related to alertness or self-consciousness levels (Kramer, 2007) and positively correlates with the underlying cortical activity and negatively with performance (Dietrich & Stoll, 2010). This desynchronization of mid-beta together with alpha desynchronization means participant experiences effortless focused attention, and relaxation without feeling one-self during the flow state to meet high task demands (Jung et al., 2000; Guo et al., 2016; Ergenoglu et al., 2004). Frontal mid-beta has commonly been associated with vigilance levels involved in a task; and has been found to be linked to self-consciousness in gameplay (Hartmann & Klimmt, 2006; Kramer, 2007).

The results obtained for mid-beta activity were significant for brain activity decrease in the flow state when compared to resting and boredom states. Berta et al (2013) while performing the spectral characterization of video-gaming experience (specifically flow, a key element in gaming experience) found that mid-beta discriminates gaming from other tasks (Berta et al., 2013). Results obtained are in line with previous research studies.

6. DISCUSSIONS OF RESULTS

The theory of effortless attention is in line with the theory of flow; these theories emphasize that users need to have the capability or skill to carry out a task in order to perceive effortless attention and autotelic experience (Csikszentmihalyi, 1975; Csikszentmihalyi & LeFevre, 1989). When a user is in the flow state, their alpha activity in the left frontal and occipital regions of the brain is low because of the high level of attention that is focused on the task at hand. Some researchers have found moderators for the effect of challenge-skill balance on flow. For example, if the perceived importance of the task is not low (i.e., moderate or high), flow can occur when the skill is higher than the challenge (Engeser & Rheinberg, 2008). Having a skill level that is higher than the level of challenge facilitates the emergence of effortless attention in the flow state where a user experiences a state of high attention that is effortless and autotelic in nature (Bruya, 2010; Dehaene et al., 1998; Nakamura & Csikszentmihalyi, 2014).

Effortless attention in the flow state gives rise to low theta activity in the left frontal region of the brain because the working memory load is decreased when one is experiencing flow. In other words, there is a decrease in theta activity in the left frontal region due to effortless or reduced action and attention, along with automaticity and spontaneity, even during high task demands. Flow and automaticity share several commonalities: transcended negative aspects of self, reduced felt effort, and positive experience (Bargh & Ferguson, 2000). Bruya (2010) has conceptualized effortlessness as spontaneity. Hence, the increase in performance during the flow state suggests a close link between expert performance and effortlessness. Although it involves intense mental activities to learn a highly refined skill over an extended period of time, task execution becomes effortless during the flow state (Davidson et al., 2003). Flow also contributes to exploratory behavior, creativity, and positive subjective behavior (Chen, 2006; Zaman et al., 2010). The optimal performance during the flow state is the result of high (but effortless) attention, decreased cognitive load, and a shutdown of external distractions by the user (Dietrich & Stoll, 2010). From the above explanations, it can be deduced that a person in the flow state experiences effortlessness, immersion, concentration, intrinsic rewards, expert performance (increased level of learning), arousal, spontaneity, and automaticity.

The correlates of the boredom state derived from the arousal and attentional theories are in line with the neural correlates that was obtained through this EEG study. Firstly, when a user is in the boredom state, their alpha activity in the left frontal region of the brain is high, representing a low attentional level or failure of attention (Fisher, 1993). The alpha activity is negatively correlated with attention. This failure of attention in the boredom state arises from a mismatch between challenge and skill (challenge < skill). In our study, participants were disinterested due to the low challenge level (i.e., Tetris at Level 1) and were not able to engage with the simulated environment. In such cases, participants tend to exhibit withdrawal tendency with a low-goal directed behavior and task-unrelated thoughts (Danckert & Merrifield, 2016).

Secondly, when a user is in the boredom state, their mid-beta activity in the left frontal region of the brain is high, representing active alertness and low performance. Mid-beta in the frontal network of the brain directly correlates with self-awareness and alertness levels and negatively correlates with the performance of a cognitive task (Kramer, 2007).

Thirdly, according to studies discussed in the literature and the Transient Hypofrontality Theory (THT), an individual in the boredom state has low theta activity over the frontal regions of the brain representing a low cognitive load. But in our study, we compared the boredom state with the flow state, and during the flow state, the memory load is expected to drop out or nullify based on the theory of effortless action and attention that is also associated with the concept of automatization (Bruya, 2010). Although the cognitive load on the frontal areas of the brain is high during boredom when compared to the flow state, it can be considered as least engaging and low frontal activity.

The results obtained in our study for the state of anxiety are in line with fMRI and EEG study results in the literature. When an individual is experiencing the state of anxiety, the EEG theta activity in the frontal-temporal network is less in the anxiety state when compared to the flow state. This result is in line with the anxiety components' effects explained by the Proficiency Efficiency Theory (PET) (Borkovec, 1994; Messina et al., 2013). As expected, the results obtained from this study for the anxiety state is in line with the effect of the anxiety explained by the processing efficiency theory. The effect is that anxiety can increase motivation levels which in turn minimizes the anxiety of individuals (Eysenck, 1992). Since frontal and temporal regions of the brain are involved in working memory tasks, the temporal lobe is associated with object processing. According to the Attentional Focus Theory (AFT), an individual with high anxiety levels can encounter stress and aggressively develop strategies to resolve the challenges posed and reduce stress/anxiety levels (Eysenck et al., 2007). Under such conditions, performance can be high with a decrease in the felt effort but negative effects like anger, frustration, worry, depression, and decreased motivation can follow (Messina et al., 2013).

This study provides encouraging and promising findings on the brain activity during the flow, boredom, and anxiety states. Utilizing interdisciplinary approaches in neuroscience and IS, this research provides an enhanced understanding of user experience in gaming from the neuroscience perspective. In addition, the findings are useful to HCI designers who can utilize EEG to assess user experience in real-time and understand the effects of different game design elements and interface (e.g., gamification features) on the flow state of users.

Although research has identified factors that contribute to flow, cognitive engagement, cognitive absorption, and immersion, the neural correlates for the flow state during HCI have only been approximated. The current literature does not offer strong or consistent empirical evidence on neural correlates of flow, boredom, and anxiety over the frontal, parietal, temporal, and occipital regions of the brain which are important for building systems that better user engagement. This research contributes to the collective effort by the research community to resolve the inconsistencies in the literature and to develop a stronger theoretical foundation to understand the flow phenomenon from the neuropsychophysiological perspective.

7. LIMITATIONS AND FUTURE RESEARCH

The present study investigated neural contributions to understand flow experience based on the more objective data recording measures than self-reported measures. A limitation of this research study was recruiting only male university students who are within the age range of 18-30 as participants. These demographic factors can be considered as pre-requisite elements for a person to experience the state of flow. This limitation not only reduces generalizability, but also motivates us to conduct a similar study with female participants to investigate gender related differences and commonalities in the neural correlates of specific user experience states. For example, Poels et al. (2012) identified the differences between motivation levels of male and female participants during gaming (Poels et al., 2013).

Future research can focus on extending the analysis of EEG spectral band activities for flow, boredom, and anxiety states over the right hemisphere of the brain and then comparing these results with the left hemisphere counterparts. Doing so can help to explain the brain activation patterns for user experience states and help researchers to identify which side of the brain depicts flow better during gaming. Further EEG flow research studies need to be conducted across various other domains beyond gaming to attain common neural correlates for the flow state. After obtaining the neural correlates of each dimension of the flow state, researchers can try to implement predictive analytics techniques to identify and classify user states based on the recorded neurophysiological signals.

Another stream of research that may help to understand the neural and physiological correlates of flow in the brain is related to meditation. Meditation practice has often been linked to the flow experience (Csikszentmihalyi, 1990; Goldberg et al., 2006) because its target has always been to attain full attentional control. Both the flow and meditation phenomena are characterized by a deep concentration on a certain focus. Once entered in a meditative state, practitioners report feelings of effortless attention which could be related to flow. However, meditation is usually practiced in the resting position whereas flow arises during an activity that might require more physiological activation. But existing studies have shown inconsistencies in the results. In some studies, increased activity in frontal lobes was found during meditation (Newberg et al., 2001; Herzog et al., 1990), which would speak against a state of hypofrontality during effortless attention. Common attributes of flow and meditation are loss of sense of time, space and self-awareness. Future research with an explicit focus on the flow experience during task performance needs to be conducted to clarify this issue.

This study provides encouraging and promising results on the brain activity in the left frontal, left parietal, occipital and frontal-temporal regions for specific bands (theta, alpha, and mid-beta) during boredom, flow, and anxiety states. It adds value to the work related to neurophysiological correlates of neuroscience.

8. THEORETICAL AND PRACTICAL IMPLICATIONS

The theoretical and practical implications of this study are discussed in this chapter. Section 8.1 briefly discusses the contribution of results to existing theory and emphasizes supporting theories and findings. Section 8.2 provides the practical implications of the research and the practices that can be implemented to better the use of this technology.

8.1. THEORETICAL IMPLICATIONS

From a theoretical standpoint, this study revealed the relationship between theta, alpha, and mid-beta bands in the left frontal, temporal, parietal, and occipital regions of the brain during resting, boredom, flow, and anxiety states of user experience. This research supports a finding that flow is associated with a positive state and corresponds with left hemisphere activity. This study also made an effort to emphasize that flow is associated with attentional levels and leads to an increase in performance. The presence of the attentional levels resembles focused attention and concentration during the flow state. The findings of this research also validate effortless theory of action and attention, processing efficiency theory, and transient hypofrontality theory. This study has furnished significant neural correlates of the flow, boredom, and anxiety states using EEG by providing theoretical support. This study fills the gap between fMRI and EEG findings over the frontal, temporal, parietal, and occipital cortices for the above-mentioned user states in gaming.

8.2. PRACTICAL IMPLICATIONS

The study results can help organizations to understand gaming experience from a user's perspective. This study primarily benefits stakeholders within the game development industry. Game designers and the management of game development companies can utilize findings from this research to obtain a deeper understanding of the user experience from their customers' perspective. This knowledge can be induced into future game design and development practices, to produce more attractive games and increase retention, which can lead to enhanced cost-efficient business strategies.

These results can be used to understand users' state of mind and experience during gaming. For example, if a user is anxious or frustrated, the system may be prompted to offer help or present the help screen. These results can also contribute to building adaptive/dynamic systems and evaluating IS. Similarly, if a player is bored by a digital/computer game, the system can trigger a change (increase) in the game difficulty level. In addition, an application that can continuously monitor a user's state of attention can be designed. Such applications can also be used to monitor the wakefulness of the personnel involved in handling tasks that are repetitive in nature and require tremendous level of consistency. EEG can be used by employees at work and can help to evaluate an employee's level of interest in the task assigned. Ultimately, this will help to sort out the staffing issues in the corporate world (assigning the right job/task to the right person).

9. CONCLUSION

Neural correlates of the flow, boredom, and anxiety states during gaming have been investigated using brain imaging techniques. The boredom state has been conceptualized as the presence of self-consciousness (high mid-beta) and attentional failure (high alpha - low attention), and it portrays high cognitive load (high theta) when compared to the flow state. The influence of the flow state on the Default Mode Network (DMN) deactivation has been demonstrated as well. Functionally, the flow condition is associated with decreasing EEG theta activity in the fronto-parietal network and showcases an increased activity in the visual attention in the occipital region of the brain. The decreased alpha value indicates the presence of attention during the flow state, also reflecting the existence of concentration but in an effortless way. The flow state is associated with positive experience in which the user is deemed to experience attention, focused immersion, arousal, decreased mental effort, and loss of self-consciousness in an effortless way. Remarkably, the brain activity is greater over the frontal-temporal network during the flow state when compared to the anxiety state. Overall, the results obtained from the study are consistent with our study proposal that resource allocation process can be automatized though enhanced attentional skills; this automatization leads to a decrease in the left hemisphere activity, especially in the frontal-parietal and frontal-temporal regions of the brain.

APPENDIX

Welcome to this session where you will be playing a computer game. Have you played Tetris before? In this study you will be playing Tetris using mouse; keyboard should not be used under any circumstances. I will be giving a brief demo of Tetris mouse controls shortly.

These are the empty spaces in the matrix and they need to be filled with bricks which would be falling in different shapes and colors. For a change in shape, you need to hover over the mouse from either left to right or right to left; and depending upon the availability of empty spaces, the shape of the bricks changes automatically. If you don't need any specific block shape, you can perform a right click operation on the mouse and this will move the current block onto the hold frame and will let you access the next block. You can see the forthcoming blocks on the left side pane. You can see your score, number of lines cleared, and game level on the right-side pane. A mouse left click on the Tetris matrix would make blocks/bricks fall faster and hence make the gameplay faster

NOTE: You should not click outside the game frame; if you do so, the game goes into a pause state and this will hinder the study and affect the setup.

This is a training session; please start playing from level 1 until the game is over. Your game scores will be recorded.

Thank You!

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