Assessing the Use of a Brain-Computer Interface (BCI) in Mathematics Education: The Case of a Cognitive Game

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Dissertation

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DECLARATION

I hereby declare that the work which is submitted here is the result of my own autonomous research. I also assert that all the sources I have used or quoted in this investigation have been designated and acknowledged by means of complete references. I further declare that the work is submitted for the first time at this university/faculty towards the ***Magister Scientiae degree in Computer Information Systems*** and that it has never been submitted to any other university/faculty for the purpose of obtaining a degree.

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SUMMARY

South Africa currently faces a huge shortage of mathematics skills, a problem commonly referred to as the “math crisis”. Researchers in South Africa have attributed the growing “math crisis” to the lack of cognitive functions among learners. However, existing solutions to address the problem have overlooked the role of cognitive functions in improving mathematics aptitude. Moreover, even though cognitive functions have been widely established to have a significant influence on mathematics performance, there is surprisingly little research on how to enhance cognitive functions (Witt, 2011). Consequently, this study had as primary objective to explore the impact of a BCI-based mathematics educational game as a tool for facilitating the development of cognitive function that enhance mathematics skills in children.

The choice of a BCI-based solution for enhancing cognitive functions stems from recent neuroscience literature that highlights the potential of BCIs as tools for enhancing cognitive functions. Existing neuroscience, psychological and mathematical education research have established a number of cognitive functions (working memory, inhibitory control, math anxiety, and number sense) that affect mathematics education. This study combined these existing paradigms with the BCI device to provide a technological solution for enhancing the basic cognitive functions that foster mathematics learning. Following these assertions, a BCI-based mathematics educational game was developed taking into account the target population (children from the ages from 9-16) and the important role of digital educational games in improving education (in this case mathematics education in particular).

Using a within-subjects short-term longitudinal research design, this study established that a BCI-based mathematics educational game could be used to significantly enhance four basic

cognitive functions (working memory, inhibitory control, math anxiety, and number sense). These four cognitive functions have been widely acknowledged as significant fundamental aspects of mathematics education. As such, adopting such a technological solution in South African schools can go a long way to address the current “math crises” by enabling educators and learners to address the issue of low cognitive functions. This study culminated with practical recommendations on how to address the “math crisis” in South Africa.

OPSOMMING

Suid-Afrika word tans gekonfronteer met ‘n groot tekort aan wiskundige vaardighede – ‘n probleem wat as die wiskunde-krises (“math crisis”) bekend staan. Navorsers in Suid-Afrika het die wiskunde-krises toegeskryf aan die tekort aan kognitiewe funksies in leerders. Bestaande oplossings het egter die rol van kognitiewe funksies in die verbetering van wiskundige aanleg, afgekeep. Alhoewel kognitiewe funksies wyd erken word in terme van die die belangrike invloed wat dit op wiskundige prestasie het, is daar verrassend min navorsing gedoen oor hoe om kognitiewe funksies te verbeter (Witt, 2011). Gevolglik het hierdie studie, as primêre doelwit, om die impak van ‘n opvoedkundige speletjie, gebaseer op ‘n brein-rekenaar koppelvlak (BRK), as hulpmiddel vir die fasilitering van die ontwikkeling van kognitiewe funksies wat die wiskundige vaardighede in kinders te verbeter.

Die keuse van ‘n BRK-gebaseerde oplossing om kognitiewe funksies te verbeter, het ontstaan uit onlangse neuro-wetenskaplike literatuur wat die potensiaal van BRKe as hulpmiddels om kognitewe funksies te verbeter, uitlig. Bestaande neuro-wetenskaplike-, fisiologiese- en wiskundige opvoedingsnavorsing het ‘n paar kognitiewe funksies (werkende geheue, beperkende beheer, wiskunde angs en syferwaarneming) wat wiskundige opvoeding affekteer, daargestel. Hierdie studie kombineer die bestaande paradigmas met die BRK-toestel om ‘n tegniese oplossing om die basiese kognitiewe funksies wat wiskunde opvoeding behels, te voorsien. Gebaseer op hierdie bewerings is ‘n BRK wiskundige opvoedkundige speletjie ontwikkel wat die teikenpopulasie (kinders tussen die oudersomme van 9 en 16) en die belangrike rol van digitale opvoedkundige speletjies in die verbetering van opleiding (in hierdie geval spesifiek wiskunde opleiding) in ag neem.

Deur ‘n binne-deelnemer (“within-subjects”) korttermyn verlengde navorsingsontwerp te volg het hierdie studie ‘n wiskundige opvoedkundige speletjie daargestel wat gebruik kan word om vier basiese kognitiewe funksies (werkende geheue, beperkende beheer, wiskunde angs en syferwaarneming) merkwaardig te verbeter. Hierdie vier kognitewe funksies word wyd erken as fundamentele aspekte in wiskundige opvoeding. Deur ‘n tegnologiese oplossing in Suid-Afrikaanse skole aan te neem kan dus ‘n groot bydrae lewer om die bestaande wiskunde-krises aan te spreek deur opvoeders en leerders in staat te stel om die aspek van lae kognitiewe funksies te addresseer. Deel van hierdie studie se einddoel was dus ook praktiese aanbevelings oor hoe om die wiskunde-krises in Suid-Afrika aan te spreek.

RESEARCH OUTPUT

An extract of this study have been published in an ISI accredited journal (Computers & Education). The full article is presented in Appendix G.

- Verkijika, S.F., & De Wet, L. (2015). Using a brain-computer interface (BCI) in reducing math anxiety: Evidence from South Africa. *Computers & Education*, *81*, 113-122.


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Using a brain-computer interface (BCI) in reducing math anxiety: Evidence from South Africa

Silas Formunyuy Verkijika, Lizette De Wet

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Highlights

- This paper confirms the view of prior studies that math anxiety can be trained and reduced.
- The study uses a novel technology (the Brain-computer interface) for training and reducing math anxiety.
- The brain computer interface solution is easier to administer unlike the solutions provided in previous studies.
- Congruent with prior studies, it is seen that math anxiety negatively affects mathematics performance.
- The findings provide empirical support for the use of BCI devices for educational purposes.

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CHAPTER ONE

INTRODUCTION

1.1. Introduction

Over the past decade, there has been an increasing interest in the use of digital educational games as a means of enhancing learning and academic attainment. According to Kebritchi, Hirumi, and Bai (2010) educators in grades K-12, college teachers, and university lecturers have intensified the experimental use of games as a tool for pursuing educational goals. Many educators have argued that games significantly engage and motivate children. Therefore, it is imperative to take advantage of these game qualities and use them to enable learning (Gee, 2007; Scanlon, Buckingham & Burn, 2005; Squire, 2003). The Federation of American Scientists (2006, p. 3) clarified that "people acquire new knowledge and complex skills from game playing, suggesting that gaming could help address one of the nation's most pressing needs – strengthening our system of education and preparing workers for 21st century jobs." One of such pressing educational need that is highly required, but significantly lacking in most countries, is mathematics educational skills.

Most aspects of mathematics skills are related to cognitive functions (Blair & Razza, 2007; Libertus & Brannon, 2009). As such, educational tools or training that aims to enhance mathematic skills need to focus on improving cognitive functions. With recent innovations in neurotechnology, non-invasive brain-computer interface (BCI) devices have been developed, and these BCI devices have the potential of improving cognitive functions. A BCI is a communication system for controlling an electronic device (e.g. a computer) based on user evoked bio-potentials. Colman and Gnanayutham (2013) define bio-potentials as electrical signals that originate from the brain and nervous system. BCIs establish a direct connection between the brain and an electronic device (Kübler & Müller, 2007). This direct communication between the brain and a computer is achieved by decoding brain signals into commands that can be understood by the computer. BCIs can either be invasive or non-invasive. Invasive BCIs require surgical removal of a section of the skull where the brain underneath needs to be accessed, while non-invasive BCIs decode brain signals using scalp recordings, and consequently do not require any surgery or medically intensive care (Hildt, 2010). It is for this reason that non-invasive BCIs have been widely adopted and deemed suitable for use by the general public for non-medical purposes.

Experts in BCI research have highlighted that BCI devices have a huge potential for altering brain activity to improve cognitive functions such as working memory, attention, and other executive functions (Plass-Oude Bos *et al.,* 2010; Van Erp, Lotte & Tangermann 2012). However, little evidence exists to support these views as the adoption of BCIs for non-medical uses are still in its infancy (Van Erp *et al.,* 2012). One way of introducing these BCI-based systems for cognitive improvement is through the gaming industry as there has been a growing interest over the past few years in using computer games for improving cognitive functions (Lee *et al.,* 2013; Nouchi, Taki, Takeuchi, Hashizume, Nozawa, Kambara *et al.,* 2013; Simpson, Camfield, Pipingas, Macpherson & Stough, 2012). Moreover, the early adoption of commercial BCIs has been in the gaming industry (Allison, Graimann & Graser, 2006; Bezerianos, 2011). Since digital educational games have been seen to play an important role in education, a BCI-based educational game that takes advantage of the cognitive abilities of a BCI device can significantly enhance the cognitive skills responsible for mathematics aptitude in children.

1.2. Previous Studies

In order to establish the context of this dissertation, prior studies on cognitive functions, educational games and mathematics education were reviewed.

1.2.1. Cognitive Functions and Mathematics Skills

Existing neuroscience, psychological and mathematical education research provides valuable information which can be combined with BCI paradigms to establish and develop concepts for cognitive educational games. Research in neuroscience has looked at the set of cognitive processes referred to as executive functions which positively impact on the development of mathematics and reading skills in children. Blair and Razza (2007) define executive functions as the shifting of awareness, working memory, and inhibitory control of cognitive processes that are used in problem solving and goal-oriented activities. Several studies (Bull & Scerif, 2001; Espy, McDiarmid, Cwik, Stalets, Hamby & Senn, 2004) have established significant positive relationships between executive functions and early mathematics ability in young children.

With regards to neuropsychology and mathematical education, number sense has been identified as an important aspect of mathematical competence (Libertus & Brannon, 2009; National Mathematics Advisory Panel, 2008). Number sense is defined in its simplest form as “the ability to approximate numerical magnitudes” (Siegler, 2009, p. 119). Libertus and Brannon (2009) established an important link between number sense (Approximate Number System) and early mathematics development in young children who have not had any form of mathematics’ training. The finding of this study raised important questions such as; can a child’s number sense be trained to improve his future mathematic abilities? (Libertus & Brannon, 2009). These findings correlate with various studies (Jordan, Glutting & Ramineni, 2010; Van Nes & De

Lange, 2007) that also highlight the significant role of number sense in developing the mathematical abilities of children. It is, therefore, not surprising that many elementary mathematics curricula in the developed world focus primarily on teaching number sense (Casey, 2004). To shed more light on the relationship between cognitive functions and mathematics, Table 1.1 below highlights selected cognitive functions and existing evidence relating the cognitive functions to mathematics education.

Table 1.1: Studies Linking Cognitive Functions with Mathematics

Cognitive Function	Researcher(s)	Year	Country	N	Result
Working Memory	Alloway	2007a	England	55	Mixed
	Bull	2008	Scotland	124	Positive
	Kyttälä, Aunio & Hautamäki	2010	Finland	116	No impact
	Alloway & Passolunghi	2011	England	206	Positive
	Witt	2011	England	38	Positive
Inhibitory Control	Blair & Razza, 2007	2007	USA	143	Positive
	Abolmaali & Memari	2013	Iran	14	Positive
	Gilmore *et al.*	2013	England	80	Positive
	Oberle & Reichl	2013	Canada	99	Positive
Math Anxiety	Maloney, Risko, Ansari & Fugelsang	2010	Canada	28	Mixed
	Wu, Barth, Amin, Malcarne & Menon	2012	USA	162	Mixed
	Zakaria, Zain, Ahmad & Erlina	2012	Malaysia	195	Positive
	Jansen, Louwerse, Straatemeier, Van der Ven, Klinkenberg & Van der Maas	2013	Netherlands	207	Positive
Number Sense	Libertus & Brannon	2009	USA	-	Positive
	Jordan *et al.*	2010	USA	452	Positive

1.2.2. Using Games for Mathematics Education

A number of studies (Begg, Dewhurst & Macleod, 2005; Chuang & Chen, 2009; Squire, 2003) have investigated the impact of computer and video games on the cognitive learning of children. Chuang and Chen (2009) established that computer based video games enhance the cognitive learning abilities of children. Studies focusing on the impact of mathematics educational computer games have established that these games significantly improve the basic mathematics abilities of the players (Jones, 2009); promote innovative mathematical thinking skills (Devlin, 2011); and help in factual recall (Klawe, 1998). According to Lee (1996), teachers of primary mathematics should take advantage of the fact that children enjoy playing games and design instructional games to motivate the children to learn. He further elucidated that a well-designed mathematical game can have a significant positive impact on both the affective and cognitive components of mathematics learning in children. This is evident in a study by Abdullah, Bakar, Ali, Faye and Hasan (2012) where a multiplication facts computer game was used to reveal a significant positive effect on the students' retention and mastery of multiplication tables. Related studies that examined the impact of mathematics educational games on student learning are presented in Table 1.2.

Table 1.2: Studies on the Impact of Games on Mathematics Development

Researcher/s	Year	Country	N	Result
Moreno	2002	USA	61	Positive
Laffery, Espinsosa, Moore & Lodree	2003	USA	187	Mixed
Young-Loveridge	2004	New Zealand	106	Positive
Lim, Nonis & Hedberg	2006	Australia	1200	No Impact
Shaffer	2006	USA	14	Positive
Lopez-Moreto, & Lopez	2007	Mexico	47	Positive

Ke & Grabowski	2007	USA	125	Positive
Robertson & Howells	2008	USA	30	Positive
Harter & Heng-Yu	2008	USA	98	Positive
Karakus, Inal & Cagiltay	2008	Turkey	1223	No Impact
Bokyeong, Hyungsung & Youngkyun	2009	Korea	123	Positive
Chun-Yi & Ming-Puu	2009	Taiwan	78	Positive
Çankaya & Karamete	2009	Turkey	176	No Impact
Kebritchi *et al.*	2010	USA	293	Positive
Burguillo	2010	Spain	246	Positive
Vos, Van der Meijden & Denessen	2011	Netherlands	235	No Impact
Nusir, Alsmadi, Al-Kabi & Sharadgah	2012	Jordan	245	Mixed

1.3. Problem Statement

Brink, Van der Walt and Van Rensburg (2006) explicate that a research study always commences with a research problem. A research problem refers to an existing issue that leads to a need for a study to either address or provide a deeper understanding of the issue (Creswell, 2014). It is, therefore, imperative to ensure that the research problem is clearly defined and articulated as this will guide the research findings and ensure they are relevant in addressing the problem. The main problem this study seeks to address is the issue of “math crisis” that has been identified in many countries around the world, with a keen interest in the South African scenario.

Mathematical knowledge is imperative for our everyday lives; however, “math crisis” has been recorded in many countries around the world (e.g. South Africa, United States, and Britain). The case in South Africa is, however, currently worse than in most countries. The 2013 and 2014 World Economic Forum (WEF) Global Information Technology Reports (WEF, 2013, 2014) rank South Africa's mathematics and science education among the worst in the world[1]. This poor state of mathematics and science education was also reported in the 2012 Annual National Assessment (ANA) by the Department of Basic Education which revealed that most South African students only scored between 0 – 29% in mathematics. Likewise, the 2013 ANA showed that only 2.1% of grade nine students scored above 50% in mathematics. Spaull and Taylor (2012) also highlighted that a high number of students in South Africa remain functionally innumerate even after six years of formal schooling (i.e. students at grade six). Furthermore, there is empirical evidence indicating that South African primary scholars have a very low understanding of basic foundational mathematical concepts (Pausigere, 2013; Schollar, 2008). The low understanding of mathematical components can be attributed to the fact that South African learners have been known to have a low level of cognitive functions (Graven, Venkat, Westaway & Tshesane, 2013; Hlalele, 2012; Kloppers & Grosser, 2010; Mutodi & Ngirande, 2014; Taylor, 2008). However, little has been done to improve the cognitive functions of learners in South Africa. One way of addressing this situation is by using mathematics educational games to increase engagement and motivation for children to develop their cognitive capabilities as a means to facilitate grasping of basic mathematical concepts.

Although the use of educational games for enhancing mathematics skills has shown an enormous potential, researchers (Bai *et al*., 2012; Bakker, Heuvel-Panhuizen & Robitzsch, 2015; Kebritchi *et al.*, 2010) have highlighted that there is still a high shortage of empirical studies to support the effectiveness of mathematics educational computer games. Also, some existing empirical studies have yielded mixed results (Din & Caleo, 2000; Godfrey & Stone, 2013; Laffery *et al.*, 2003),

[1] In the 2013 report, South Africa is raked at position 143 out of 144 countries. Similarly, in the 2014 report, South Africa is ranked in position 148 out of 148 countries.

and most novel computer games (e.g. BCI-based games) are yet to be tested. The existing empirical evidence has focused on post-game mathematics tests for evaluating the impact of the game, while little has been done on actually evaluating the impact of the games on enhancing the cognitive functions of the players. This is a gap that needs to be filled since cognitive functions have been established to explain the differences in mathematics skills from early childhood to adulthood.

Witt (2011) has also argued that there is unexpectedly little research examining the possibility of increasing young children's cognitive functions. If we are to fully comprehend the impact of mathematics educational games in enhancing mathematics skills, it is imperative to examine which cognitive functions are stimulated or enhanced by these games. Furthermore, a comprehensive research by prominent experts highlighted that interface heuristics was the most important factor in evaluating educational games and as such it is possible that the disparities in the usability of different games could account for the mixed empirical findings on the impact of mathematics educational games. Since the impact of novel games that utilise BCIs on mathematics education have not been examined, it is important to bridge the gap as BCI-based games can provide usability feedback as well as develop the cognitive functions required for mathematics education at the same time.

1.4. Research Questions

Research questions usually originate from the identified research problem. Wood and Ross-Kerr (2011, p. 2) define a research question as "an explicit query about a problem or issue that can be challenged, examined, and analysed, and that will yield useful new information". Having a clear and concise researchable question is the most important factor in shaping a researcher's choice of research design, data collection, and analysis (Brink *et al.,* 2006). Based on the problem identified, the following research questions were formulated to guide this study:

- Can a BCI-based mathematics educational game significantly enhance selected cognitive functions that account for mathematics performance in children?
- Can a BCI-based mathematics educational game be used to improve math fluency/performance in children?
- Does the usability of an educational game (based on physiological and subjective measures) impact on the game player's cognitive functions?
- How do specific brain waves (Alpha, Beta, Theta, Alpha, Delta, and Gamma) affect the cognitive functions of the game player; and do the usability of the game determine the brain wave frequencies that dominate during gameplay?
- How does the player's level of engagement, frustration, meditation, and excitement relate to the selected cognitive functions that enhance mathematics skills?
- What is the impact of the selected cognitive functions on mathematics performance?

1.5. Objectives

Research objectives usually stipulate the specific aims of the research (Hanson, 2006). It is always important to clearly state research objectives as they are active statements depicting how the study will answer the established research questions (Brink *et al.,* 2006; Farrugia, Petrisor, Farrokhyar & Bhand, 2010). In this study, the primary objective was to explore the impact of a BCI-based mathematics educational game as a tool for facilitating the development of cognitive functions that enhance mathematics skills in children. In order to achieve this primary objective, the following secondary objectives were pursued.

- To review the literature of BCI systems with a particular interest in BCI's for gaming, usability, and education.
- To review the literature on using games for educational purposes with a particular interest in mathematics educational games.
- To examine the objective measures of cognitive functions using a non-invasive BCI device (Emotiv EPOC).
- To determine the impact of a BCI-based system on the training and improvement of the selected cognitive functions that enhance mathematics skills.
- To examine the influence of affective mind states on cognitive functions.
- To determine the relationship between brain activity (Alpha, Beta, Theta, Alpha, Delta, and Gamma) and the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense).
- To determine the impact of affective states and cognitive functions on mathematics performance.

1.6. Research Hypotheses

A research hypothesis can be defined as "a specified testable expectation about empirical reality that follows from a more general proposition. It is a statement of something that ought to be observed in the real world if the theory is correct" (Babbies, 2008, p. 45). Research hypotheses are used in transforming the research problem into predictable outcomes that are based on theoretical considerations (Brink *et al.*, 2006). Hypotheses basically postulate causal or correlative relationships between the variables in the research study (Nicholas, 2008). In order to address the research questions, the following research hypotheses were examined.

- ***Hypothesis One:*** Short term playing of a BCI educational game does not enhance selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense).
- ***Hypothesis Two:*** There is no relationship between brain activity (Alpha, Beta, Theta, Alpha, Delta, and Gamma) and cognitive functions (working memory, inhibitory control, math anxiety, and number sense).
- ***Hypothesis Three:*** The user's cognitive functions are not influenced by his/her affective state of mind.
- ***Hypothesis Four:*** There is no relationship between the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) and mathematics attainment.

1.7. Research Methodology

This study adopted a short-term longitudinal research approach in which each participant was expected to complete two BCI game testing sessions that took place on two separate days. A longitudinal research design was chosen because it was necessary to collect data from the same sample at two or more different points in time in order to determine the changes in cognitive functions with the BCI neuro-feedback. A key aspect of a longitudinal research design is the time factor. However, time factor is not only measured based on the duration of the study. Researchers (Karapanos, Martens & Hassenzahl, 2009; Singer & Willett, 2003) have argued that one way of measuring time in a scientific study is to look at it in terms of the number of data gathering waves. This typically looks at how many data gathering waves occur in a single session or across several sessions which could all span in the same day or across several days. Tullis and Albert (2013) adopted a similar view in explicating how learnability can be measured in usability studies. Prior literature and empirical findings indicated that scientific longitudinal studies should have at least three data gathering waves in order to effectively capture change (Karapanos *et al.*, 2009; Karapanos, Zimmermann, Forlizzi, & Martens, 2010; Singer & Willett, 2003). These approaches have been successfully used in many scientific studies. For example, Rieger (2009) demonstrated that change process in a longitudinal study could be sufficiently observed within a 2.5 hour session with several data gathering waves. Combaz *et al.* (2013) used two BCI session with each session lasting between 1-2 hours (if the participant was not tired) in order to evaluate change process with regards to BCI performance and cognitive workload of two spelling BCI applications.

Based on these arguments, this study adopted an approach with two sessions per participant that took place on two separate days. Each session had four data gathering waves for the selected cognitive functions, with a break (distracter task) after the second data gathering wave. The participants played two levels (level one and level five) of the BCI-based cognitive game (Math-Mind Game). These two levels varied in difficulty based on the mathematics problems they presented. The game had four key mathematics problems which were addition, subtraction, division, and multiplication. During each session, the participants played each of the two levels twice with data captured during each level. Feedback to the participant was provided after the task was completed to see his/her overall level of cognitive functions during the task and to provide personalised feedback on how to control and enhance the different cognitive functions.

1.8. Tools and Data Analysis

Several tools were used in this study to support the development of cognitive functions, capturing of research data, and analysing the captured data. The main tools used included the BCI Math-Mind cognitive game (application developed by the researcher); Emotiv EPOC (a BCI device developed by Emotiv Systems); EEGLAB, EDF Browser; and Statistical Package of Sciences (SPSS). Subjective data was captured using a pre-test, post-task, and post-test questionnaire (Appendix C, Appendix D & Appendix E respectively) and analysed using SPSS. Physiological data and data relating to brain activity and cognitive functions were captured with the Emotiv EPOC and Math-Mind game. Several statistical analyses were used to analyse the captured data in order to attain the stated research objectives. Both descriptive and inferential statistics were used in this study. The key analysis methods used included: paired sample t-test, independent sample t-test, Analysis of Variance (ANOVA), Pearson correlation, and Regression.

1.9. Ethical Clearance

It is of utmost importance to conduct research in an ethical manner in order to minimise risk/harm while endeavouring to attain benefits (Campbell & Groundwater-Smith, 2007; Sargeant & Harcourt, 2012). Taylor and Francis (2013) accentuate that it is unacceptable to proceed with any form of human research without ethical clearance. The ethical clearance process ensures that participants are given full ethical consideration, especially in the areas of informed consent, anonymity, risk, and the ability of participants to withdraw from the study at any time without penalty (Sargeant & Harcourt, 2012; Taylor & Francis, 2013).

In the process of completing this dissertation, full ethical clearance was sought from the Ethical Committee of the Faculty of Natural and Agricultural Sciences at the University of the Free State. The ethical clearance approval letter is presented in Appendix F. Also, accompanying documentation such as the letter to parents/guardians and consent form are presented in Appendix A and Appendix B respectively. It was acknowledged that this study posed minimal or no risk to the participants and adhered to all the ethical considerations.

1.10. Contributions of the Study

Over the years, researchers have highlighted the importance of using multimedia technology as a means to aid human cognition (Mayer, 2005). With the recent innovations in commercial non-invasive BCI technologies, there is a higher possibility of enhancing cognitive functions with these tools. Research on systems that enhance cognitive functions can provide valuable solutions in addressing the “math crisis” problem in South Africa, as the poor mathematics performance among South African learners has been attributed to learners having very low levels of cognitive functions (Graven *et al.*, 2013; Hlalele, 2012; Kloppers & Grosser, 2010; Mutodi & Ngirande, 2014; Taylor, 2008). This study will thus contribute in addressing the shortage of mathematics skills in South Africa by providing solutions for developing and enhancing the cognitive functions that significantly improve mathematics aptitude.

Furthermore, researchers have highlighted that the societal relevance and economic viability of using BCI applications for education is quite high. However, Van Erp *et al.* (2012) have highlighted that research on the use of BCI technology for educational purposes is still limited. This study will contribute in this domain by evaluating the impact of the use of a BCI for educational purposes. Also, it has been seen that most studies on the impact of games and cognitive functions on mathematics have been done in Europe, America, and Asia with little or no studies in this domain yet to emerge from the African continent. This study will contribute to the bulk of knowledge by providing empirical evidence on the subject from an African perspective.

1.11. Chapter Outline

This dissertation comprises of six chapters. Chapter one provides a detailed background as a means of establishing the context on which the study is based. Also included in this chapter are the research problem, research questions, research objectives, research hypothesis, brief description of the methodology, and a brief overview of the tools and data analysis methods used in this study. Moreover, issues relating to ethical clearance and contributions of the study were discussed.

Chapter two and chapter three concentrate on providing a thorough literature review on selected aspects pertaining to this dissertation. In chapter two, literature on the history of BCI technologies, the functioning of a BCI system from signal acquisition to controlling an application, the different brain signals used for BCI operations and several uses of a BCI system are presented. In Chapter three, a detailed review of the relationship between mathematics educational games and mathematics attainment is provided. Also, the chapter elaborates on the impact of the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) on mathematics performance.

Chapter four focuses on the research design and methodology. The selected research design is discussed in detail with other key aspects of the methodology such as the sampling process, measurements, data collection techniques, and research protocol. In chapter five, the findings from the data analysis are presented.

Finally, chapter six provides the conclusions and recommendations drawn from the study. The chapter also explicates how each objective was achieved, how conclusions were derived from the hypotheses, details the significance of the study, provides practical recommendations for addressing the “math crisis” problem, and concludes with limitations and arenas for future studies.

1.12. Summary

This chapter provided the background to the study by introducing the key concepts that pave the way for the study. The chapter highlighted that most aspects of mathematics skills are related to cognitive functions. Also, it was shown that educational computer games are becoming increasingly important in enhancing mathematics skills. As a result, the possibility of using a BCI-based system as a means of enhancing cognitive functions could have a significant effect on the development of mathematics skills in children. This is because of the BCI’s ability to enhance cognitive functions. Based on these concepts, a problem statement, research questions, and the research objective were established. Similarly, the ethical aspects and contributions of the study were discussed. Furthermore, the chapter outline for the dissertation was provided. A combination of the issues discussed in this chapter raises a need for the study as can be seen in the contributions of the study. The next chapter will focus on a literature review on BCI technology and its uses.

CHAPTER TWO

BRAIN-COMPUTER INTERFACE (BCI) TECHNOLOGY

2.1. Introduction

This chapter commences with an overview of BCI technologies and then moves forward to provide a brief history of BCIs. It introduces the reader to the key components of a BCI system such as signal processing, signal acquisition and BCI applications. The Different kinds of BCI systems that can be used for capturing real-time brain signals and neurological impulses from the user are presented. Likewise, the different BCI applications that translate the brain signals into useful real-world commands to control a system are explained. The chapter presents details of the different brain activities that are used for controlling BCI devices. Lastly, the uses of BCI systems with the selected domains being health and medicine, usability, cognitive enhancement, and gaming are highlighted. A mind-map of this chapter is presented in Figure 2.1 below for quick recall and reference purposes.

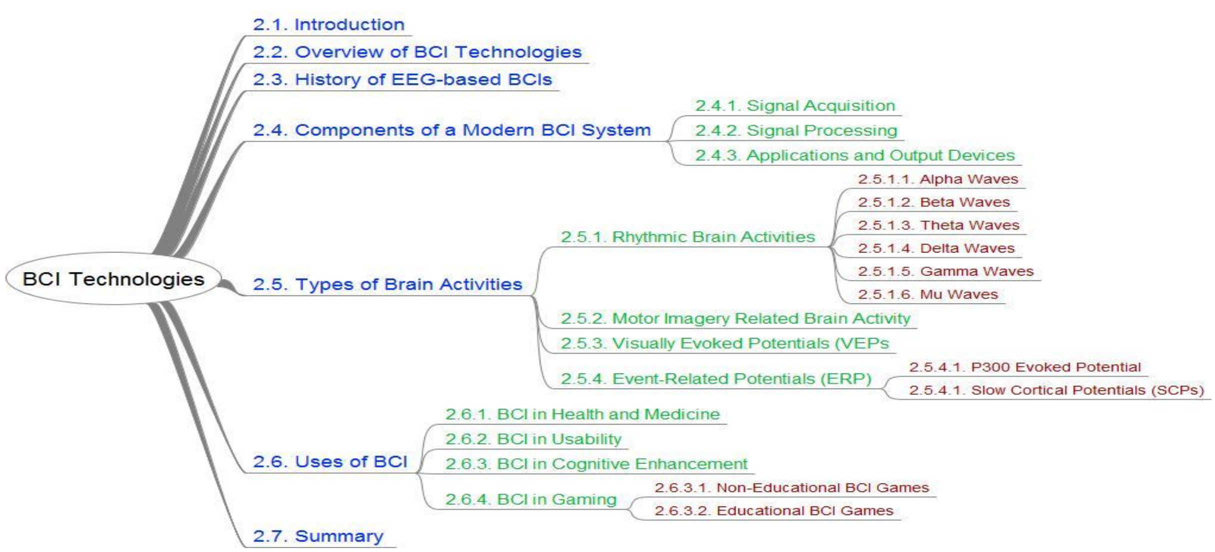


Figure 2.1: Mind-map of Chapter Two

2.2. Overview of BCI Technologies

A BCI is a communication system for controlling an electronic device (e.g. a computer) based on user evoked bio-potentials. Bio-potentials are electrical signals that originate from the brain and nervous system (Colman & Gnanayutham, 2013). Wolpaw, Birbaumer, McFarland, Pfurtscheller and Vaughan (2002) define a BCI as a communication system in which the commands or messages sent by an individual to the external world do not pass through the normal output channels of brain communication such as peripherals (e.g. speech) and muscles (e.g. gestures). Instead, a BCI device uses any bio-potentials that are under the conscious control of the user (Gnanayutham & George, 2006). BCIs establish a direct connection between the brain and an electronic device (Kübler & Müller, 2007). This direct communication between the brain and a computer is achieved by decoding brain signals into commands that can be understood by the computer. BCIs can either be invasive or non-invasive. According to Hildt (2010) invasive BCIs require surgical removal of a section in the skull where the brain underneath needs to be accessed, while non-invasive BCIs decode brain signals using scalp recordings (EEG-based BCIs) and therefore do not require any surgery or medically intensive care. Figure 2.2 shows an overview of how the components of a BCI system function together.

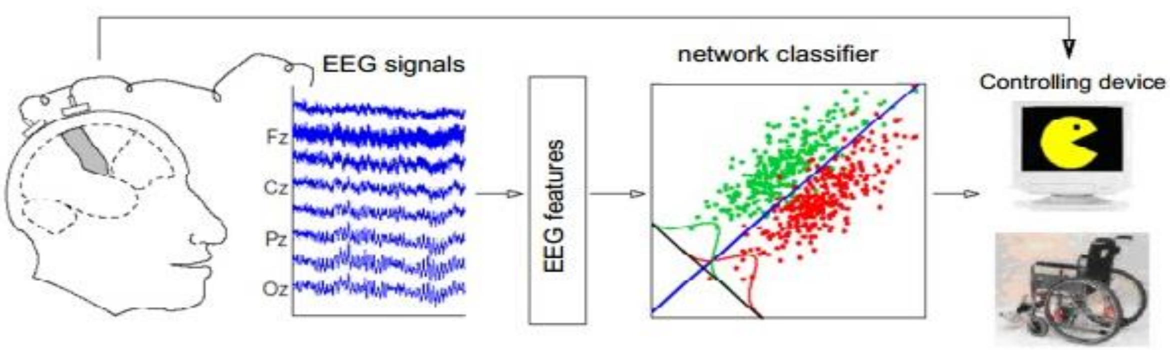


Figure 2.2: Schematic view of BCI System (Source: Karlovskiy & Konyshev, 2007: 16)

For the purpose of this study, only non-invasive BCI devices will be considered. In this regard, the different bio-potentials that can be recorded are: electroencephalography (EEG), electromyography (EMG), magnetoencephalogram (MEG), and near-infrared spectroscopy (NIRS). The definitions for these bio-potentials are provided in Table 2.1 below:

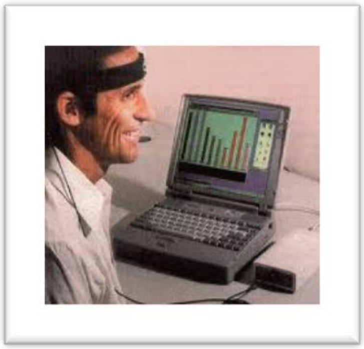
Table 2.1: Description of Bio-potentials used in Non-Invasive BCIs

Bio-potential	Definition	Source
EEG	Measurement of electrical waves generated by the brain.	Akay (2007)
EMG	Measurement of the electrical signals originating from muscle movement involving neuromuscular physiology.	Kamen & Gabriel (2010)
MEG	"Brain signals that result from extracranial magnetic fields produced directly by intracellular neuronal currents."	Wyllie, Cascino, Gidal & Goodkin (2010, p. 871)
NIRS	Optical method used for measuring localised cortical brain activity.	Coyle, Ward & Markham (2007)

From the list of bio-potentials in Table 2.1, only the EEG will be explored in detail for the purpose of this study. EEG-based BCIs have shown enormous potential and interest from the research community because of its wide array of potential uses (Campbell *et al.*, 2010; Chae, Jeong & Jo, 2012; Choi & Jo, 2013). The software application developed for the purpose of this study is based on an EEG BCI device (Emotiv EPOC) which was the only kind of BCI system available to the researcher. As such, availability of the EEG-based BCI device is one of the reasons why this dissertation focuses primarily on the EEG brain activity. Different types of BCI devices exist and serve various purposes such as playing games, carrying out research, and assisting in medical rehabilitation. Some of the commercially available BCI devices that measure non-invasive bio-potentials are presented in Table 2.2 Below.

Table 2.2: Commercially available BCI devices

Name of BCI device	Manufacturer	Sample Image	Key Features
EPOC	Emotiv		• 14 sensors plus 2 references offer optimal positioning for accurate spatial resolution. • Gyroscope generates optimal positional information for cursor and camera controls. • Hi-performance wireless technology gives users total range of motion. • Dongle is USB compatible and requires no custom drivers. • The Lithium Battery provides 12 hours of continuous use. (Emotive, 2014).

Mindwave	NeuroSky		• It has one dry sensor that can be placed on the left side of the forehead. • Three dry sensors on the left ear, for reference. • It has a microchip which pre-process the EEG signal, and transmits the data via bluetooth (Neurosky, 2014)
Cyberlink™ Mindmouse	Brain Actuated Technologies Inc.		• A headband with three sensors detects electrical signals on the forehead resulting from subtle facial muscle, eye, and brain activity. • Decodes the forehead signals into ten BrainFingers for continuous cursor control (Cyberlink, n.d).
Enobio®	Starlab		• Has a 0 to 250 Hz bandwidth which allows the user to record EEG in all bands. • 8 or 20 channels (32 optional). • Bluetooth for data transmission (Ectron, 2014).

Neural Impulse Actuator™	OCZ Technology		• Three neural sensors. • Eyebrow movement detection (APC, 2012).

2.3. History of EEG-based BCIs

Birbaumer (2006) states that the origin of BCIs can be traced back as far as 1929 when Hans Berger uncovered the human EEG and proposed the possibility of using complex mathematical analysis to read thoughts from the EEG signals. Berger later discovered that EEG signals varied with a person's mental state and that the signals from each mental state could be read from the human skull and represented graphically on paper (Forslund, 2003). Some of the mental states that Berger examined included: sleeping, neural diseases (e.g. epilepsy), lack of oxygen and anaesthesia. He was the first person to refer to the human brain bio-potentials as "electroencephalogram". In 1964, Grey Walter developed the first automatic frequency analyser which was used to discern thoughts and language in the human EEG (Kotyra & Wójcik, 2010). Further research by Walter led to the development of the first multi-channel EEG device (Toposcope). In 1973, a more innovative version of the first advanced BCI devices was created. This version was referred to as a "carrier(s) of information in man-computer communication or for the purpose of controlling such external apparatus as a prosthetic device or spaceship" (Vidal, 1973, p. 157). Since then, there has been continuous growth in BCI research and development with many organizations developing novel approaches for measuring brain activities for use in BCI systems.

2.4. Components of a Modern BCI System

A BCI system is made up of several components such as the input device for reading the user's EEG activity (neuro-headset), computer, EEG amplifier, and EEG software. The components of a BCI system can be divided into three main categories namely: signal acquisition, signal processing, and applications and output devices. An illustration of these categories is presented in Figure 2.3 below.

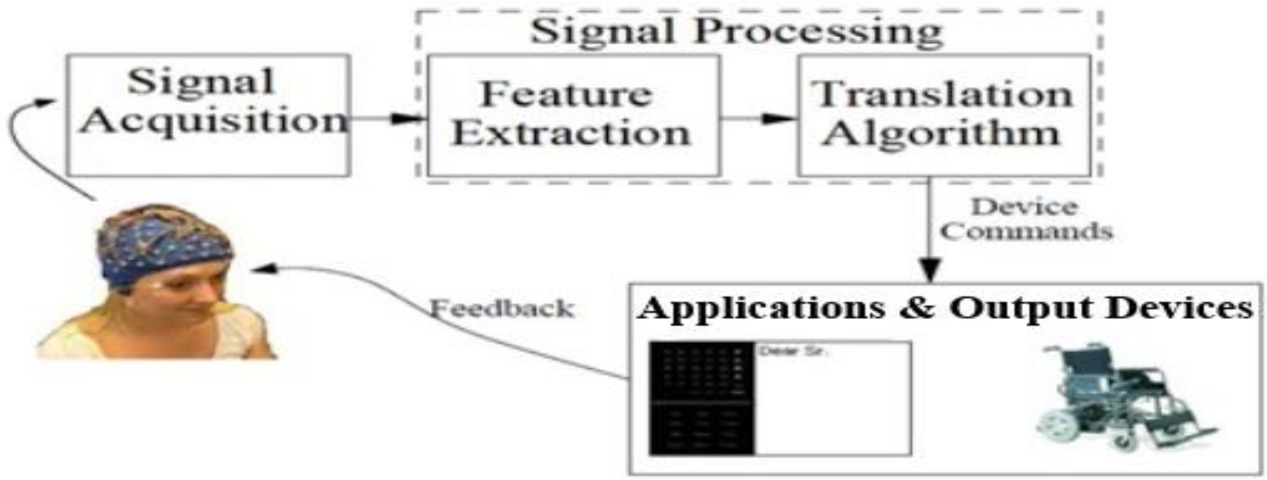


Figure 2.3: Components of a BCI System (Source: Cabrera, 2009: 13)

All these categories function together following a systematic approach from acquisition of bio-potentials from the brain and converting them to provide feedback on a screen or to control an end device. Each of these categories of the BCI systems will now be discussed in detail.

2.4.1. Signal Acquisition

As mentioned in section 2.2, a BCI system acquires brain signals using either an invasive or a non-invasive method. Signal acquisition generally refers to the methods by which signal-to-interference (S/I) ratio and signal-to-noise (S/N) ratio can be enhanced, while also ensuring an ideal combination of temporal and spatial information (Ochoa, 2002). S/I ratio refers to the proportion of the power of the true signal to the power of the estimated signal corrupted by interference (Cichocki, Zdunek, Phan & Amari, 2009), while S/N ratio refers to the average power of the message signal at the receiver output to the average power of noise at the receiver output (Chitode, 2007).

Signal acquisition is usually achieved with the aid of specially built electrodes that are optimized for capturing brain activity. Basically, three things happen during the signal acquisition stage. Firstly, the electrodes acquire the brain signals either through scalp recordings or invasive methods; secondly, the BCI system amplifies the acquired signals; lastly, the brain signals are converted into a digital format that can be understood by electronic systems. Table 2.3 below depicts some of the most common methods of signal acquisition and their vital characteristics as applied to a BCI system.

Table 2.3: BCI Signal Acquisition Methods

Signal Acquisition Method	Bio-potentials measured	Temporal Resolution	Spatial Resolution
	Invasive BCI Signal Acquisition Methods		
Electrocorticogram (ECoG)	Electric potentials	Very high	High
Microelectrode Arrays	Electric potentials	Very high	Very high
	Non-Invasive BCI Signal Acquisition Methods		
EEG	Electric potentials	Very high	Low
MEG	Magnetic fields	Very high	High
NIRS	Hemodynamic Act	Low	Very low

With invasive signal acquisition methods, the electrodes are surgically implanted into the brain tissue from the cerebral cortex (Rao, Rajyalakshmi & Prasad, 2012). The invasive signal acquisition techniques provide brain signals of very high quality; however, the fact that they require surgery before use is one of the key problems to this approach that discourage its use. Non-invasive BCI acquisition techniques on the other hand are more conducive for use in practical situations because they capture electrophysiological brain signals using scalp recordings. Of all the mentioned system acquisition methods, EEG is the most widely used. This is because of its low cost, high real-time resolution, ease of use, and the fact that it is non-invasive (Cabrera, 2009). Furthermore, EEG meets all the BCI specifications for use in practical situations (Rao *et al.,* 2012). For these reasons, as well as because of its affordability, this study is based on EEG data.

After acquiring the EEG data from the subject, it is then forwarded to the signal processing unit where information is extracted from the EEG data.

2.4.2. Signal Processing

According to Krusienski *et al.* (2011), signal processing is the most important part in the design of a successful BCI system. Signal processing in a BCI system is composed of two key steps, namely: feature extraction and translation. Firstly, the EEG signals need to be filtered so that the required features can be extracted from the acquired EEG data. This stage is important because EEG recordings, in addition to electrical signals, also contain numerous unwanted signals such as EMG signals originating from muscular activity, interference from electrical equipment, and other signals arising from eye movements (Rao *et al.,* 2012). Secondly, translation algorithms are used to classify the brain signals and convert them into commands that can be understood by the output application or device. These two stages of signal processing are explained in detail below.

2.4.2.1. Feature Extraction

This stage of signal processing involves the extraction of required features from the acquired and amplified EEG signal. Wolpaw *et al.* (2002) elucidate that this stage always involves selecting a desired frequency range and amplitude based on some reference measurement level. Frequency ranges are used for feature extraction because the EEG signals acquired from the subject always contain periodic waveforms that are of the same frequency as the stimulus (Muller & Hillyard, 1997). The BCI feature extractor mechanism transforms the selected frequency ranges that correspond to the user induced neurological mechanisms and outputs a feature vector (Ghumman, Singh & Ghumman, 2013). The feature vector is what is then sent to the translator for classification and decoding into reasonable control signals. Examples of widely used feature extraction methods are presented in Table 2.4 below.

Table 2.4: Feature Extraction Methods

Feature Extraction Method	Description
Spectral parameters	This method computes the frequency components by approximating the power density spectrum of the EEG signal and averaging the spectral components around the target frequency (Muller-Putz, Scherer, Brauneis & Pfurtscheller, 2005).
Time–frequency (TF) analysis	In TF analysis, the distribution of the power of EEG signal is calculated as a function of both time and frequency (Qin & He,

	2005).
Cross-correlation-based template matching (CCTM)	In CCTM, an EEG signal template is generated from the test data by averaging the triggered signals and the decision feature is formed by cross-correlating the EEG template with the signals from the test data (Huggins *et al.*, 2003).
Signal envelope-cross correlation	In this method, EEG signals are broken down into sequences of frequency bands. The instantaneous power of each band is then denoted by an envelope of oscillatory activity (Wang, Deng & He, 2004).
Hjorth parameters	This method characterizes EEG signals in terms of the variance of the signal, mean frequency, and deviation from the sine shape of the signal oscillations (Boostani & Moradi, 2004).
Stepwise discriminant analysis	In this method, input features if the EEG signals are weighted using ordinary least-squares regression to determine the target class label (Donchin, Spencer & Wijesinghe, 2000).

Irrespective of the feature extraction method used, it is important to ensure that the selected method is accurate and robust as this enables the translation stage to produce correct and reliable actions, as well as ensures that the user feedback is as natural as possible (Wolpaw & Wolpaw, 2012).

2.4.2.2. Feature Translation

The BCI classifiers or translation algorithms receive the feature vector from the feature extraction method and then use it as input for classifying the signals into control actions (e.g. cursor movement). Lehtonen (2002) notes that these BCI translation algorithms vary greatly from simply linear models to complex nonlinear algorithms with each one trained to recognize a different mental task. Examples of linear classifiers include: fisher linear discriminant analysis (FLD), linear discriminant analysis (LDA), and Bayesian classifiers. Examples of widely used non-linear classifiers include: support vector machine (SVM) and neural networks (Cabrera, 2009). In several cases, different algorithms are used with each one representing a particular class of BCI signal. When this approach is used, the feature vectors are classified using predefined probability functions to determine which class it belongs to by choosing the class with the highest probability (Millán *et al.*, 2002; Wolpaw & Wolpaw, 2012). Furthermore, the translation algorithm compensates for impulsive changes in brain signals by using a whitening procedure such as linear transformation to produce signals with a defined variance and zero mean (Schalk & Mellinger, 2010). These transformed signals ensure that the output application or device does not have to account for changes in brain signals which are unrelated to the desired mental task. The desired brain signals obtained from the translation algorithms are always classified into six important categories based on either their frequency or shape (Chandrakar & Kowar, 2012; Rosso *et al.,* 2001). These categories are: Beta waves, Alpha waves, Theta waves, Delta waves, Gamma waves, and Mu waves. Each of these categories of BCI signals are discussed in detail in section 2.5.1.

2.4.3. Applications and Output Devices

The potential uses of a BCI system in controlling various applications and output devices are enormous. Several end user applications and output devices have been developed that use BCI signals to perform particular actions. In most cases, a computer screen is considered as the output device. With computer applications, some of the BCI actions can include: selecting an object or text (Citi, Poli, Cinel & Sepulveda, 2008; McFarland, Krusienski & Wolpaw 2006), moving a cursor (Lehtonen, 2002), typing text (Birbaumer *et al.,* 1999), playing video games (Krepki, Blankertz, Curio & Mueller, 2007; Mason, Bashashati, Fatourechi, Navarro & Birch, 2007), or navigating web browsers (Karim *et al.,* 2006; Surdilovic & Zhang, 2006). Other non-computer based output devices can include: controlling a wheel chair (Rebsamen *et al.*, 2006), controlling electrical appliances (Bayliss, 2003; Gao, Xu, Cheng & Gao, 2003), or controlling robots (Millan, Renkens, Mourino & Gerstner, 2004; Potgieter, 2013; Taylor, Tillery & Schwartz, 2002). After understanding the key components of a BCI system and how it works, it is important now to understand the brain activities that BCI systems use in controlling these output devices.

2.5. Types of Brain Activities

An understanding of the brain and its functioning played a critical role in the design of BCI devices. In the early years of EEG discovery, as explained in section 2.3, Burger noticed that different actions and stages of consciousness were associated with different EEG signals (Birbaumer, 2006). Since then, research (Awang, Pandiyan, Yaacob, Ali, Ramidi, & Mat, 2011; Lehtonen, 2002; Luu, Tucker & Makeig, 2004; Sherman *et al.,* 2011) has shown that different actions stimulate certain parts of the brain, which is why the brain signals vary. In order to measure these different brain activities, researchers established a functional brain map that indicates all the components of the brain so that brain activity from these sections can be measured. Figure 2.4 below depicts a functional brain map.

Functional brain mapping has received a lot of interest from the research community as Lancaster *et al.* (2000) noted over 250 published studies on functional brain mapping. However, the details of the different sections of the functional brain map are outside the scope of this study.

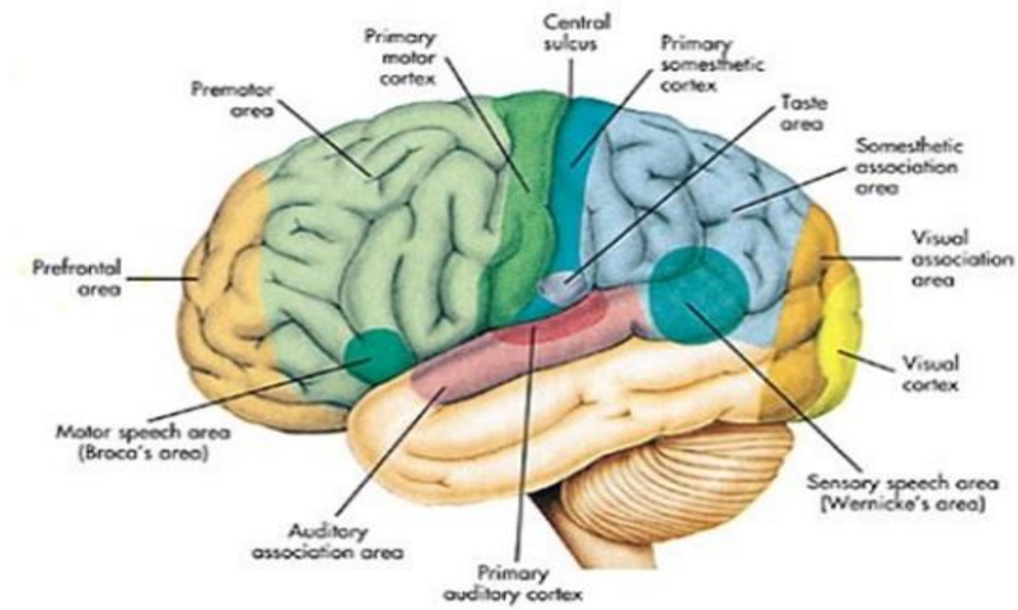


Figure 2.4: Basic Functional Brain Map (Source: Larsen, 2011: 12)

Nonetheless, it is imperative to mention the role that functional brain mapping has played in advancement of BCI technology. This can be seen in the development of standards for electrode placements in a BCI for measuring the different brain activities.

Since prior research identified that different parts of the brain provided different brain frequencies, a standard known as the 10-20 standard was developed to facilitate measurement of brain activity in the different regions of the brain (Larsen, 2011).

The BCI system used in this dissertation (Emotiv EPOC) is based on the 10-20 standards and captures brain activity from all the areas indicated in the functional brain map above. Figure 2.5 below shows the 10-20 system as depicted by the Emotiv EPOC control panel indicating the signal acquisition from the 14 sensors placed in the 10-20 locations.

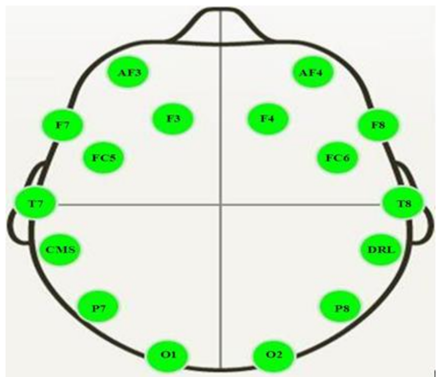


Figure 2.5: Emotiv EPOC Sensors in the International 10-20 Locations

The different brain signals that can be captured from the various sections of the brain include: rhythmic brain activity, event-related potentials (ERP), motor imagery-related brain activity, and visually evoked potentials. Figure 2.6 below provides a visual description of how the different brain activities are discussed in this chapter.

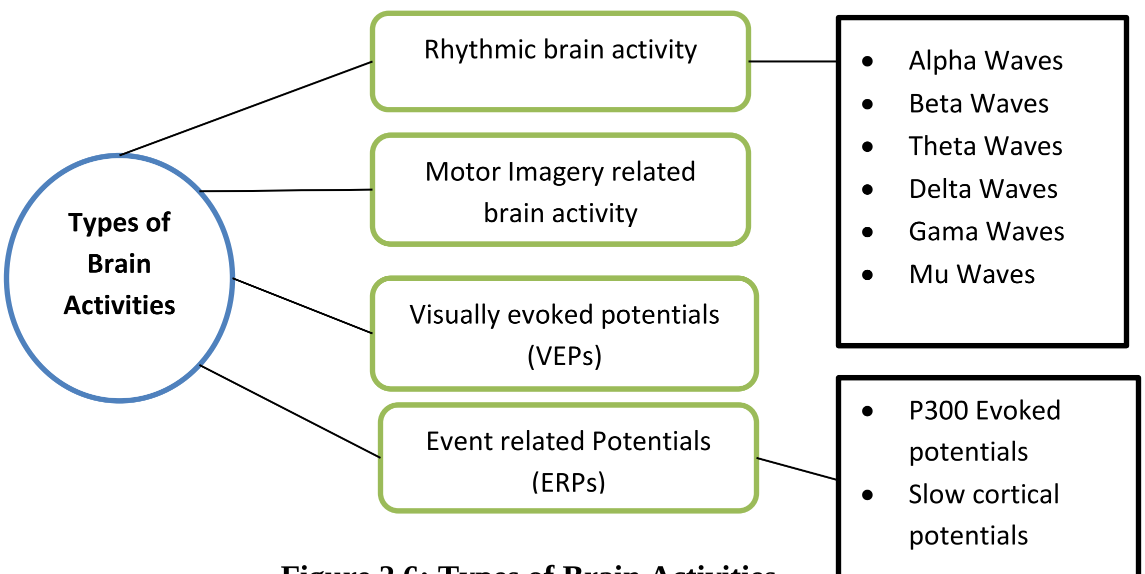


Figure 2.6: Types of Brain Activities

2.5.1. Rhythmic Brain Activities

Steriade (2004, p.1) defines rhythmic brain activity as "regularly recurring waves of similar shape and frequency." Rhythmic brain activities were the first type of brain activities to be recorded as EEG data in humans (Gladwin, 2008). Examples of rhythmic brain activity include: Alpha waves, Beta waves, Theta waves, Delta waves, Gamma waves, and Mu waves. These rhythmic brain activities are discussed below.

2.5.1.1. Alpha Waves

Alpha waves are a combination of rhythmic activities of the cerebral cortex (i.e. all the sensory, motor, and association areas depicted in Figure 2.4) with a frequency range between 8 and 13 Hz and amplitude of about 30 to 50 μV (Kasprzak, 2013; Rao *et al.*, 2012). According to Nishifuji, Ohkado and Tanaka (2006), Alpha waves are the most prominent component of brain waves. Kirschefeld (2005) observed that Alpha wave activity in EEG is made up of both linear and nonlinear components. He elucidated that the linear components arise from evoked potentials while nonlinear components are mainly due to light adaptation. Apha wave activity is usually dominant when a person is in a conscious state of mind (Sherman *et al.*, 2011). Some of the stimuli that have been known to cause changes in Alpha wave frequency and amplitude include: mental arithmetic, memory tasks, sound, and light (Schaul, 1998). Mathewson, Gratton, Fabiani, Beck & Ro (2009) also indicated that Alpha wave oscillations significantly influence the awareness of visual targets. Alpha waves are usually induced by some form of alertness or mental concentration. One use of Alpha wave fluctuations, especially in the frontal lobes, has been to examine a person's psychological state of mind (Yoshida, 1998). An example of Alpha waves is depicted in Figure 2.7 below.

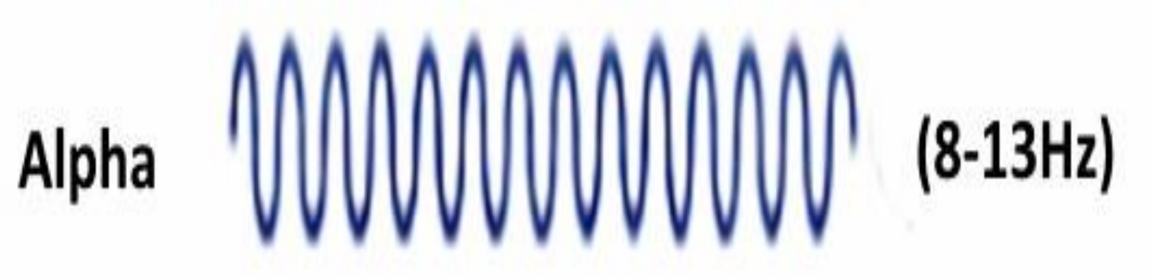


Figure 2.7: Alpha Brain Waves (Source: Rao *et al.,* 2012: 20)

2.5.1.2. Beta Waves

Beta waves are brain waves with a frequency between 13 and 30 Hz and always have very low amplitudes ranging from about 5 to 30 μV (Lehtonen, 2002; Ochoa, 2002; Rao *et al.,* 2012). Beta waves can sometimes reach 50 Hz during periods of intense brain activities. These waves are mainly encountered over the central and frontal brain regions (Schomer & Da Silva, 2011). Beta wave frequencies are sometimes separated into frontal Beta, posterior Beta, diffuse Beta, and central Beta. According to Aparnathi and Dwivedi (2013), Beta waves are usually dominant when people are active or excited. Almost every healthy adult has some level of Beta activity. Stern (2005) highlights that Beta brain activity is usually less than 20 μV in about 98% of healthy awake subjects with over 70% having less than 10 μV. An example of Beta waves is depicted in Figure 2.8 below.

Figure 2.8: Beta Brain Waves (Source: Rao *et al.,* 2012: 20)

2.5.1.3. Theta Waves

Theta waves have a frequency range between 4 and 7 Hz and amplitude of about 20 μV. Roa *et al.* (2012) highlight that Theta waves are usually produced when the brain is under stress, emotional tension, disappointment, or frustration. These waves are generated during the time when a person is under deep meditation. Theta waves are largely dominant around the 7Hz frequency range. It has been widely established that Theta waves over the frontal midline region of the brain have a significant correlation with mental tasks such as problem solving (Awang *et al.*, 2011; kropotov, 2009; Kubota *et al.*, 2001; Lehtonen, 2002; Luu *et al.*, 2004). Rodriguez-Martinez, Barriga-Pauline, Rojas-Benjumea and Gomez (2013) found that Theta brain activity had comparably higher relationship strength with working memory during childhood development compared to other brain activities. Likewise, Raghavachari *et al.* (2001) indicated that Theta brain activity played a vital role in organizing multi-item working memory. An example of Theta brain activity is depicted in Figure 2.9 below.

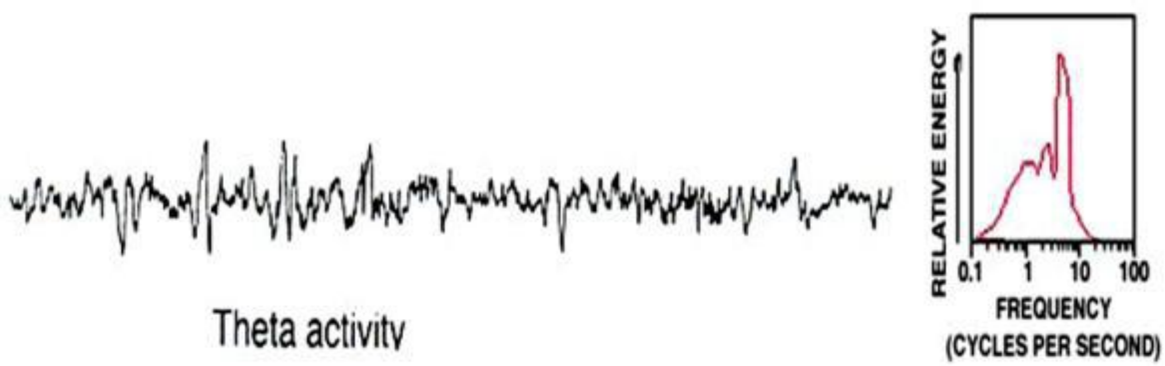


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Figure 2.9: Theta Brain Waves (Source: Rao *et al.*, 2012: 20)

2.5.1.4. Delta Waves

Russell, Hertz and McMillan (2011) explicate that Delta waves are high amplitude brain activity with frequency ranges between 0 and 4 Hz. Delta brain activity is mostly associated with deep-sleep states (Halasz & Bodizs, 2013). Delta waves are associated with decision and it has been seen that the amplitude of Delta brain waves increases considerably during cognitive functions (Basar, Basar-Eroglu, Karakas & Schurmann, 2001). Knyazev (2012) showed that Delta waves play an important role in motivation, attention, subliminal perception, and salience detection. Delta waves have been noted to be important in cognitive functions only during developmental stages when the brain is still in the maturation state (Knyazev, 2012). This is because during adulthood, the Delta waves are mostly seen only during deep sleep (Rial *et al.*, 2007). For this reason, some researchers (Lehtonen, 2002) have argued that the fact that Delta waves are only seen in deep sleep in adults makes the Delta brain activity less important for BCIs that are used by adults. Another drawback of Delta brain activity in BCI use is the fact that they are easily contaminated by artefacts such as jaw and eyeball movements (Ahn, Cho, Ahn & Jun, 2013). An example of Delta brain activity is depicted in Figure 2.10 below.

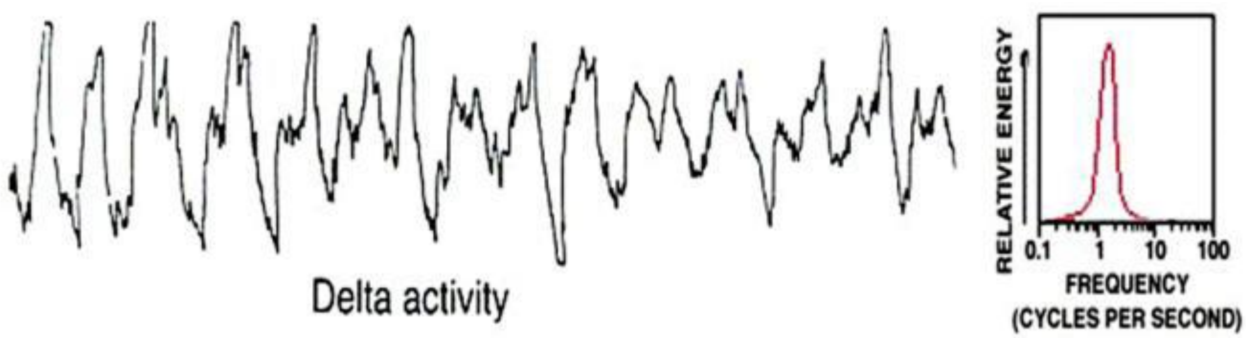

Figure 2.10: Delta Brain Waves (Source: Rao *et al.*, 2012: 20)

2.5.1.5. Gamma Waves

Gamma waves usually have a frequency range of 30Hz and above. Gamma waves hardly occur alone as they are often supported by Alpha, Beta, and Theta waves (Trevisan & Jones, 2012). Rangaswamy *et al.* (2002) found that Beta waves are strongly associated with cognition, attention, and perception. Also, many studies (Lutz, Greischar, Rawlings, Ricard & Davidson, 2004; Vialatte, Bakardjian, Prasad & Cichocki, 2009) have shown that Gamma brain activity is usually observed during meditation. An example of Gamma brain activity is depicted in Figure 2.11 below.

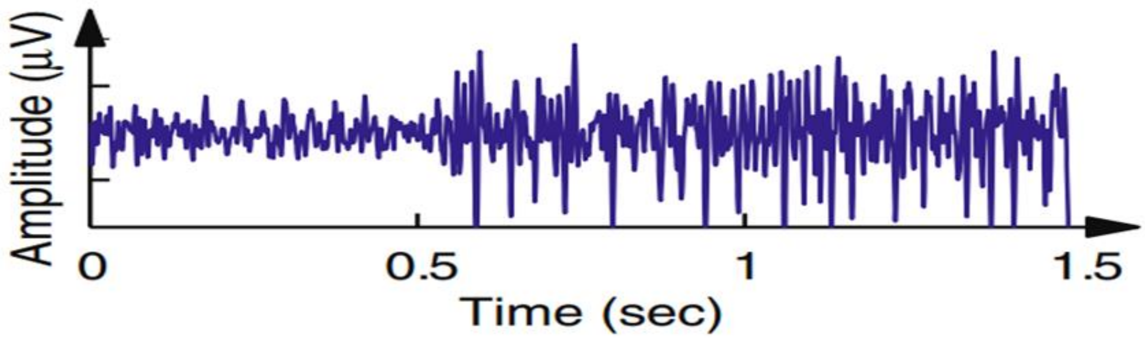

Figure 2.11: Gama Brain Waves (Source: Vialatte *et al.*, 2009: 985)

2.5.1.6. Mu Waves

Mu waves have a frequency range within the Alpha band (8-13Hz); however, they are independent of the Alpha waves and are mainly evoked during the execution or perception of actions such as motor activities (Andreassi, 2006; McGarry, Russo, Schalles & Pineda, 2012). Mu waves appear over the sensorimotor area (Figure 2.4) of the brain and are usually recorded at the vertex of the scalp making them very useful in on-invasive BCI devices. Pineda (2005) elucidates that Mu waves are sensorimotor brain activities that consist of several frequencies having different origins, both in the motor areas and parietal sensory areas. Matsumoto, Fujiwara, Takahashi, Meigen, Kimura & Ushiba (2010) highlighted that Mu waves are usually present in about 50-100% of healthy subjects. Some BCI applications have been designed to use Mu waves. For example, Pineda, Silverman, Vankov and Hestenes (2003) designed a first-person shooter game that used the mu waves to control movement. In the game, the left and right rotations were controlled by “low” and “high” Mu respectively. Several researchers (Muthukumaraswamy, Johnson & McNair, 2004; Nystrom, Ljunghammar, Rosander & von Hofsten, 2011) have shown that Mu waves are more modulated during goal directed actions.

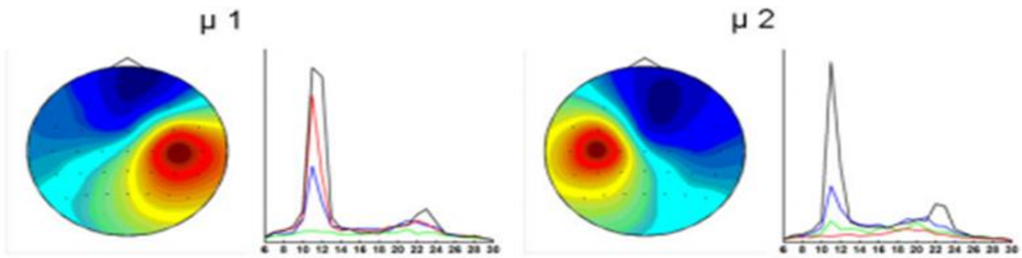

Figure 2.12: Mu Brain Waves (Source: Frolov *et al.*, 2012: 7)

Figure 2.12 depicts the Mu brain acitivity during imagined moverment. μ_1 shows the mu brain activity when imaginning moving the left hand, while μ_2 shows the Mu rhythm when imagining moving the right hand.

2.5.2. Motor Imagery Related Brain Activity

The second kind of brain activity is the motor imagery related brain activity. Motor imagery related brain activity refers to the activation of brain waves in a subject’s motor cortex as a result of simulating an action using the brain without actually performing it. This type of brain activity is also known as motor-related brain activity. Pfurtscheller and Nerper (2001) view motor imagery as the mental rehearsal of a motor action without the production of any real motor output. Motor imagery produces self-induced variations of EEG by modifying neuronal activity in the primary sensorimotor areas in a similar manner as done by real executed movement (Miller, Schalk, Fetz, den Nijs, Ojemann & Rao, 2010; Yi, Qiu, Qi, Zhang, Wan & Ming, 2013,). The use of motor-related brain activity in the development of BCIs is based on the fact that the spatial distribution of EEG differs for different imagined movements (Wang, Hong, Gao & Gao, 2007). For example imagining lifting the left hand produces different EEG signals from imagining lifting the right hand. Motor imagery based BCI devices have been seen to be very useful in training subjects for the improvement of basic motor skills.

In medicine, Scherer, Mohapp, Grieshofer, Pfurtscheller and Neuper (2007) elucidate that motor imagery based BCIs have been used for the rehabilitation of stroke patients. Another avenue where motor imagery based BCIs are being utilized is in sports for training athletes, as evidence has shown that these BCIs enhance their performance (Hwang, Kwon & Im, 2009; Li, Pan, Wang & Yu, 2013). Motor imagery based BCIs are widely used in robotics to control robots and artificial human parts. For example, Potgieter (2013) and Dollman (2014) used a BCI to control a robot. The difference between the two studies is that while Potgieter (2013) focused only on forward and backward movement, Dollman (2014) included turning left and right to navigate the robot along a pre-defined path. Do, Wang, King, Chun and Nenadic (2013) used motor imagery to control robotic gait orthosis. A robotic gait orthosis is a device (e.g. prosthetic legs) that is applied externally on someone to modify the person's functional abilities related to neuromuscular and skeletal system.

2.5.3. Visually Evoked Potentials (VEPs)

The fourth kind of brain activity is the VEP. VEPs are electrical-potential differences that are derived from the scalp after a subject experiences a visual stimulus such as a flash-light (Prueckl & Guger, 2009). These signals are generally separated into two main categories namely: transient VEPs and steady state VEPs (SSVEP). The transient VEPS have a frequency range less than or equal to 3.5Hz, while the SSVEPs are those with a frequency greater than 3.5Hz (Luck, 2005). Paulus (2005) indicates that SSVEPs are more useful in BCIs because of their steady nature. This steady nature of SSVEPs causes individual responses to overlap, thereby resulting in a quasi-sinusoid oscillation[2] that has the same frequency as the stimulus.

A SSVEP is a recurring response to a repetitive visual stimulus having a higher frequency but with a constant amplitude and phase over a noticeably long period (Malik, Gupta, Bansal & Rathore, 2007; Wong, Wang, Wan, Mak, Mak & Vai, 2010). Xu, Li, Gu and Xia (2012) argue that SSVEP-based BCI systems are widely used because of their numerous advantages such as high transmission rates, less training, easy detection of signals, and wide applicability. Additionally, Vialatte, Maurice, Dauwels and Cichocki (2010) indicated that SSVEPs were highly used in BCI systems because of their high S/N ratio. Lalor *et al.* (2004) showed that SSVEP-based BCI systems had a high performance level in a real-time gaming framework. Combaz *et al.* (2013) also achieved a high performance level with a SSVEP-based BCI for text spelling.

2.5.4. Event-Related Potentials (ERP)

The fifth type of brain activity is the ERP. ERPs are "very small voltages generated in the brain structures in response to specific events or stimuli" (Sur & Sinha, 2009, p. 70). Mugler *et al.* (2008) note that ERPs usually occur about 300 milliseconds from when a subject is presented with an unexpected stimulus, thus permitting a stimulus to be distinguished from others. These ERPs are produced by a wide array of cognitive, sensory, and motor events. Grierson and Kiefer (2011) argue that ERPs are highly used in BCI research because of their high reliability in deciphering cognitive processes. Nicolaou, Nasuto and Georgiou (2008) supported this view by

[2] A quasi-sinusoid oscillation has the same appearance as a sinusoid (sine wave) oscillation but varies relatively slowly in frequency or amplitude (Griffin, 2004).

elucidating that many BCI devices are based on ERPs because ERP signals have specific and distinguishable characteristics that are recognizable by the BCI system. Two of the most widely used ERPs for BCI applications are P300 and Slow Cortical Potentials (SCPs). These two ERPs are explained below.

2.5.4.1. P300 Evoked Potential

The P300 is a positive ERP that is evoked at intervals of 300 ms and matches meaningful external stimuli with the subject's attention (Khan, Farooq, Akram, Choi, Han & Kim, 2012). P300 BCI applications follow the 'oddball paradigm'. What this means is that a P300 potential is produced whenever a subject encounters a vital rare stimulus in a sequence of stimuli (Fabisch, Kassahun, Wohrle & Kirchner, 2013).

One area where P300-based BCIs have been widely used is in applications that deal with conveying verbal information, such as spelling and text writing. This is because P300 has been established to be functionally superior to other BCI communication channels because of its higher rate of information transfer (Jin, Sellers & Wang, 2012). Evidence from numerous researchers (Donchin *et al.,* 2000; Mayaud, *et al.,* 2013) has shown that P300 ERPs are extremely useful in acting as a communication channel for patients with severe muscular or neurological disorders. Shahriari and Erfanian (2013) found that a P300 had an average accuracy of 97.5% for detecting a character in a BCI Speller application and 90.5% for character recognition. A BCI Speller application refers to a BCI system that is used to spell characters. A sample P300 recorded stimuli is presented in Figure 2.13 below. The figure depicts the scalp topographic mapping of P300 responses peak amplitude (Mayaud, *et al.,* 2013).

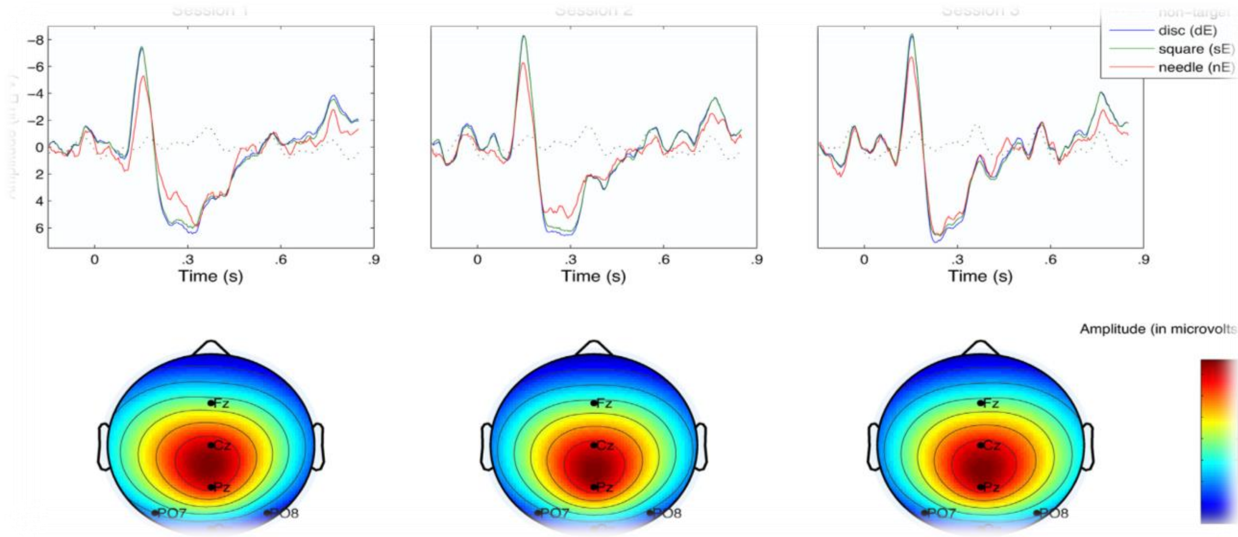

Figure 2.13: Sample P300 Recoding (Source: Mayaud *et al.*, 2013: 223)

2.5.4.1. Slow Cortical Potentials (SCPs)

SCPs are special types of ERPs measured in terms of slow direct EEG current shifts depicting the excitation threshold potential of the upper cortical layer of the brain (Gani, Birbaumer & Strehl, 2008). The excitation threshold potential is the transmembrane voltage level to which any further depolarization will initiate an action potential (Sanei, 2013). BCI devices always measure SCPs by determining the movement of the EEG signals. A shift of EEG signals in the electrical positive direction indicates an increase in excitation potential, while a shift in the electrical negative direction reflects a decrease in excitation potential. When a brain is functioning normally, positive SCPs are associated with mental preparation, while negative SCPs are associated with mental inhibition (Wolpaw & Wolpaw, 2012).

Prior BCI research (Birbaumer, 2006; Chatelle, Chennu, Noirhomme, Cruse, Owen & Laureys, 2012; Neumann, Hinterberger, Kaiser, Leins, Birbaumer & Kübler, 2004) has shown that people can train their brains to control SCPs and use it to operate several applications. SCP-based BCIs have been used to develop Speller and internet browsing applications for patients with Amyotrophic Lateral Sclerosis (ALS) (Birbaumer, 2006; Hinterberger, Kubler, Kaiser, Neumann & Birbaumer, 2003). A key advantage of using SCPs for BCI applications is their ability to remain very stable over a longer period of use (Chatelle *et al.,* 2012). However, SCP-based BCIs have a major drawback as they require very long periods or user training which can at times be several months (Birbaumer, 2006; Hinterberger, Veit, Wilhelm, Weiskopf, Vatine, & Birbaumer, 2005). A recorded SCP stimulus of a subject controlling cursor movement is depicted in Figure 2.14 below. The figure can be viewed as three sections. The far left section depicts the topographical distribution of SCPs while the middle sections depict the time function for two tasks (dashed line represent negative task while solid line represents positive task). The far right represents the time difference between the two tasks.

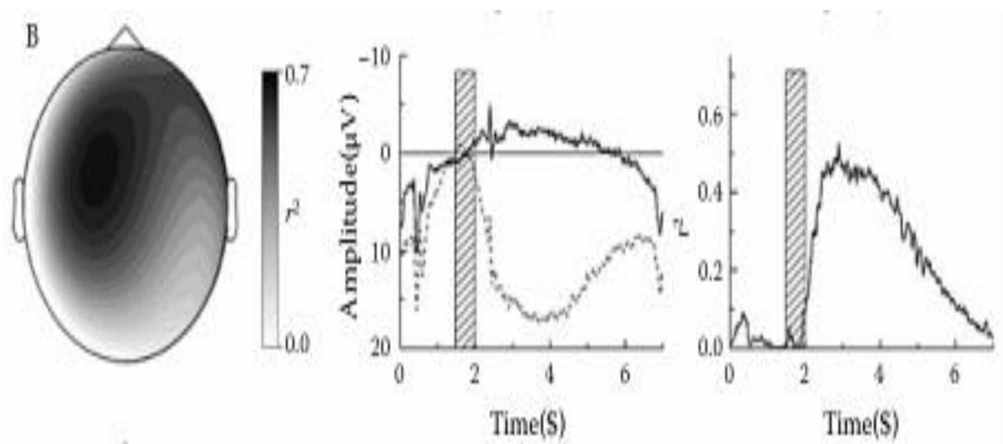

Figure 2.14: Sample SCP Recording (Source: Dilorenzo & Bronzino, 2008: 12-8)

2.6. Uses of BCI

Early BCI applications were developed primarily as medical applications for assistive care as a means of providing an alternative communication channel for the physically impaired, physically challenged, or locked-in users (Van Erp *et al.,* 2012). However, recent advancements in BCI technology have led to the development of innovative non-medical applications for use by healthy users (Sellers, Vaughan & Wolpaw, 2010; Van Erp *et al.*, 2012). BCI devices are used in a wide array of domains such as health and medicine, sports, usability (including affective computing), gaming, education, cognitive enhancement, and user state monitoring. However, for the purpose of this study, only the domains applicable to this research will be discussed. Figure 2.15 below depicts the key uses of BCI devices that will be discussed in this section.

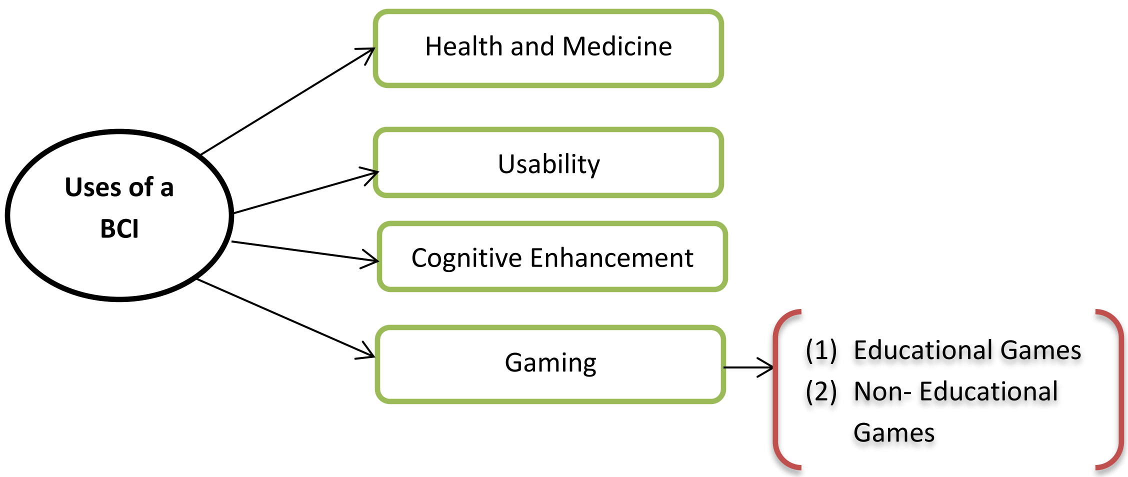

Figure 2.15: Selected Uses of BCI

Of the four uses of BCI in Figure 2.15, only health and medicine do not directly apply to this dissertation. However, it is important to review literature on BCI uses in health and medicine as it was the first field to actively engage in BCI use. Even today, most BCI applications are still used for medical purposes (Collinger, Boninger, Bruns, Curley, Wei & Weber, 2013; Müller-Putz, Schreuder, Tangermann, Leeb & Millán, 2013). Moreover, non-medical BCI applications such as applications for cognitive enhancement, usability, and gaming have adopted BCI paradigms that have been used and proven to be successful in medical applications.

2.6.1. BCI in Health and Medicine

The first BCI systems for medical use have mostly focused on providing people with some form of disability with a restorative means of gaining back mobility, as well as helping those with physiological disorders to be able to perform certain tasks (Hoffmann, Vesin, Ebrahimi & Diserens., 2008; Nijholt, Tan, Allison, Milan & Graimann, 2008). Neuro-imaging research over the past two decades has clearly established the existence of hidden awareness in numerous patients with disorders of consciousness (Chatelle *et al.*, 2012). It is in this light that many BCI systems have been developed to exploit the potential of diagnosis in patients with several brain disorders or locked-in syndrome. According to Alwasiti, Aris and Jantan (2010), the most important target group of BCI users are patients. For patients with physical disabilities, P300-based BCI devices have been shown to be a promising non-muscular communication tool for controlling several end user devices/applications (Sellers & Donchin, 2006). Hinterberger *et al.* (2003) have also commended the valuable contribution of BCI devices in the medical communities for acting as communication channels for locked-in patients with no means of muscle activity. BCI systems have also been used as hands-free neuroprosthesis command tools for aiding patients with spinal cord injuries suffering from tetraplegia to be able to carry out daily activities by controlling devices with the BCI (Boord, Barriskill, Craig & Nguyen, 2004; Postelnicu, Talaba & Toma, 2010).

BCI systems have also been used in the medical community for treating Attention Deficit Hyperactivity Disorder (ADHD) (Lim *et al.*, 2012). ADHD is a chronic condition (symptoms such as inability to control behaviour, difficulty in paying attention and staying focused, and hyperactivity) that results from childhood developmental disorders and sometimes extends to adulthood (Biederman, Petty, Evans, Small & Faraone, 2010; Mick, Byrne, Fried, Monuteaux, Faraone & Biederman, 2011).

Malik *et al.* (2007) utilised a BCI application, called a thought translation device, with patients with severe psychiatric and neurological disorders like chronic epilepsy that has been classified as untreatable. These researchers showed that patients with these chronic conditions could successfully communicate with other people using a BCI device and a virtual interface. Moreover, BCI systems have been used in clinical situations for prediction of epileptic seizures (Guo, Rivero & Pazos, 2010). Likewise, Hochberg *et al.* (2006) successfully developed a BCI system that was used by paralyzed patients to control cursor movements on a screen. Birbaumer (2006) as well established that EEG-based BCI devices successfully acted as communication channels for paralyzed patients. Researchers at the Australia National University have developed a BCI system that helps in assisting patients with vision impairment by stimulating the retina (Barnes, 2012). Furthermore, Carabalona, Castiglioni and Gramatica (2009) used several experiments to establish that BCIs could be successfully used as neurorehabilitation tools in clinical settings.

2.6.2. BCI in Usability

This dissertation follows the standard ISO 9241-11 definition for usability as “the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use” (ISO/IEC, 1998). The BCI device has enormous potential for use in the domain of human-computer interaction (HCI) and usability in particular. One usability testing method for HCI designs that has widely been used for measuring the user experience is the classification of mental workload (Tan & Nijholt, 2010). The development of the BCI device has made it easier for researchers to classify mental workloads during usability tests with high accuracy levels. For example, Grimes, Tan, Hudson, Shenoy & Rao (2007) recorded a 99% accuracy rate when using a BCI device to classify mental workload during a usability test.

Information about the mental state of the user when interacting with a system can be very useful in optimizing the design of the user interfaces. Blankertz *et al.* (2010) highlights that mental states such as emotion, fatigue, workload, and levels of arousal can be used for enhancing suboptimal user interfaces as a means of increasing the effectiveness of production systems. The researchers further showed that an EEG-based BCI system could be effectively used to gather this information. Cutrell and Tan (2008) have noted that prior to the development of the BCI, it was extremely difficult to obtain direct information of a user's cognitive workload such as to know exactly how difficult it was for the user to perform a given task. Nonetheless, researchers over the years have been using several behavioural and physiological measurement techniques for inferring cognitive processes. For example, the eye gaze and mouse movements have been used to measure attention, while the galvanic skin repose and heart rate have been used for deducing physiological arousal and fatigue. These measures have been widely used because of their perceived usefulness in usability studies (Kitamura, Yamaguchi, Imamizu, Kishino & Kawato, 2003). Researchers (Jatzev, Zander, DeFilippis, Kothe, Welke & Rötting, 2008; Zander, Kothe, Welke & Roetting 2008) have supported the accuracy of measuring these cognitive processes with BCI devices. The fact that a BCI device can accurately capture the cognitive information that is highly desirable in usability studies makes the device a valuable tool in usability studies.

In addition to cognitive information, Tan and Nijholt (2010) explicated that information about the affective state of a user is also very important when evaluating the user experience. Some of the affective state components that have been widely used in usability include: frustration, engagement, excitement, delight, surprise, immersion, surprise and anxiety (Cutrell & Tan, 2008; Reuderink, Nijholt & Poel, 2009; Tan & Nijholt, 2010; Van Erp *et al.,* 2012). According to Tan & Nijholt, (2010) BCI devices have proven to be a fast and sensitive toll for directly discerning the affective states of users. Some studies (Liu, Agrawal, Sarkar & Chen, 2009; Obaid, Han & Billinghurst, 2008) have supported the value of the BCI affective state for HCI studies by providing empirical evidence. With the presence of low cost non-invasive BCI devices, it is likely that the adoption of BCIs in usability will increase. For example, research studies (Potgieter, 2013; De Wet, Greeff & Nel, 2012; Dollman, 2014) have used the low cost Emotiv EPOC BCI for usability purposes by examining the user's affective state of mind when performing a given task. Potgieter (2013) and Dollman (2014) evaluated the usability of a system that uses an Emotive EPOC BCI to control a Lego robot. De Wet *et al.* (2013) captured the user's affective mind state while the user interacted with a social network across different platforms (e.g. mobile and PC). Furthermore, Dollman (2014) indicated that the Emotiv EPOC BCI is intuitive to use and can be suitable for use as a natural user interface (NUI). NUI generally refers to a means of supplementing or replacing traditional input methods like the mouse and keyboard with alternatives like brain signals, gestures, and speech recognition (Hearst, 2011; Sorel, Kulpa, Badier & Multon, 2013).

2.6.3. BCI in Cognitive Enhancement

Researchers (Devlin, 2014; Saniotis, 2009; Van Erp *et al.,* 2012) have asserted that BCI systems have a great potential for improving cognitive functions such as attention, working memory, and executive functions. However, these researchers acknowledge that there is little experimental data at the moment to ascertain the impact of BCIs on enhancing cognitive functions. This is one of the gaps that will be filled by this dissertation. Lee *et al.* (2013) provided empirical evidence on how a BCI application for the elderly (ages 60 and above) was used to significantly improve the cognitive functions of the participants. These researchers focused on the different aspects of working memory and attention and found significant improvements in all of these factors. The results of this study were the first pilot findings of an ongoing study and further results will be published after completing the final study. Thomas, Vinod and Guan (2013), using five healthy subjects, showed that playing a BCI game has a significant positive impact on enhancing attention and memory skills.

2.6.4. BCI in Gaming

It has become evident in recent years that BCI technology can be used in games to offer users a more affluent experience and new models of interacting with computers and game consoles (Van de Laar, 2009). Currently, a number of BCI games exist that are based on either actual or imagined movements. Nijholt *et al.* (2008) highlights that game companies have taken a keen interest in BCI for gaming which has led to the development of games in which healthy users employ BCI technologies to control movements in virtual environments. BCI games are generally classified according to existing BCI paradigms which are feedback games, imagined movement games and ERP games. Notwithstanding the BCI paradigm used, Nijholt *et al.* (2008) note that it is important to develop the BCI games to be multimodal so as to incorporate a secondary control device, as BCIs alone are not fully responsive to be used as the only game control. In this project, the focus will be on implementing an educational BCI game. Thus, the subsequent literature will be discussed in terms of non-educational and educational BCI games.

2.6.4.1. Non-Educational BCI Games

One of the early BCI games was developed by Pineda *et al.* (2003) and was designed as a first-person shooter game. In this game, the user employed a BCI input device for imagined movements when turning around and the keyboard for other movements. The ability of a user to control his/her Mu rhythm enabled the player to turn right or left. As mentioned in section 2.5.1.6, the mu rhythm refers to a kind of brain wave rhythm that can be measured with EEG (Pineda *et al.*, 2003). The left and right rotations were controlled by "low" and "high" Mu respectively.

Mühl *et al.* (2010) developed a BCI game called "Bacteria Hunt" which utilized a P300 paradigm. These researchers used this game to test the possibility of using P300 in games by evaluating how the stimuli could be used to change the angle, size and colour of visual bacteria in the game. The best results were obtained for changing the colour of the stimulus.

"Mind the Sheep" is also another non-educational BCI game that has received considerable attention in the literature of BCI gaming (Gürkök, 2012; Plass-Oude Bos *et al.*, 2010). In this game the game player has to herd a flock of sheep using many dogs and fence them as quickly as possible. The player selects a dog using the BCI device and then selects the position where the dog should move to with a mouse. The "Mind the Sheep" game is an evoked response game based on the steady-state visually evoked potential (SSVEP) (Gürkök, 2012). As mentioned before, the advantage of SSVEP is that it allows a higher number of commands compared to other BCI paradigms (Martinez, Bakardjian & Cichocki, 2007).

Another non-academic BCI game is the BCI Dolphin game developed by Rapoport *et al.* (2008). With the BCI dolphin game, the user controls a dolphin under the water to eat swimming fish.

The user performs a specified cognitive task in order to raise or lower the dolphin. Figure 2.16 provides a screen capture of the BCI Dolphin game.

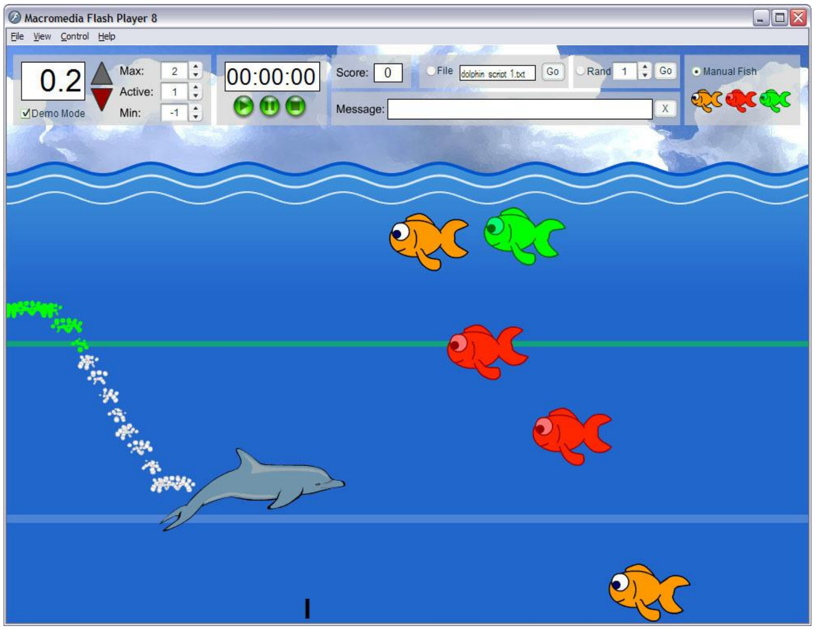

Figure 2.16: Screen Capture of "BCI Dolphin" Game (Source: Rapoport *et al.*, 2008: 592)

In addition to the above, a good number of other non-educational BCI games have also been developed and tested. A brief overview of these games is provided in Table 2.5

Table 2.5: Overview of Non-Educational BCI Games

BCI Game	BCI paradigm used	Source
Nero feedback training game based on EEG	Feedback	Allanson and Mariani (1999)
Brainball - Controlling a ball on a table during relaxation	Feedback	Hjelm and Browel (2000)
Brainathlon – Open source game for Nero feedback training	Feedback	Palke (2004)
3-D “Mindbalance” game – Player uses brainwaves from left and right cerebral	Feedback	Shim, Lee and Shin (2007)
3D game based on SSVEP	ERP	Lalor *et al.* (2004)

BCI game in which user navigates a small car on the screen in real time	ERP	Martinez *et al.* (2007)
BCI game using imagined movement to turn the avatar left.	Imagined Movement	Mason, Bohringer, Bprisoff and Birch (2004)
Grid game using BCI to move a cursor to a target while avoiding traps.	Imagined Movement	Kayagil *et al.* (2009)
BCI Pacman game	Imagined Movement	Krepki *et al.* (2007)
Finger movement BCI game	Imagined Movement	Lehtonen *et al.* (2008)
BrainBasher – Imagined movement of left or right index finger	Imagined Movement	Plass-Oude Bos and Reuderink (2008)

Source: (Compiled from existing studies)

2.6.4.2. Educational BCI Games

Educational games (also known as learning games) are defined as "games that create appealing and immersive learning experiences for delivering of specified educational/learning objectives, outcomes or experiences" (De Freitas, 2006, p. 9). Educational games usually have cognitive, behavioural, emotional and/or social dimensions which are associated with educational goals. According to Van Erp *et al.* (2012) research on the use of BCIs for educational purposes is still in its infancy. However, the societal relevance and economic viability of using BCI applications for education is quite high. These researchers also note that BCIs have the capability of improving the cognitive capabilities of healthy users and this can be very useful for educational purposes. Wang and Jung (2011) note that the use of BCIs can enhance the effectiveness of education and training by enhancing and monitoring a student's attention/concentration as well as the aptitude to participate effectively. While most of the assertions about the use of BCIs for educational purposes are still lacking significant empirical evidence, it is a motivation for this dissertation to contribute to the development of an application (BCI game) which is tested in this dissertation to provide empirical evidence on the use of BCIs for educational purposes.

Existing BCI educational games currently available in the Emotiv (Emotiv, 2014) and Neurosky (Neurosky, 2014) application stores include SpeedMath, Schulte, Mind Hunter, MindBlaster, and Focus Pocus. SpeedMath is a BCI educational game bundled with the Neurosky Mindwave BCI. The game helps in the training of arithmetic skills and also monitors the student's level of attention when carrying out arithmetic tasks. Schulte is a BCI game for training the attention levels of the players. The game consist of a 5x5 grid containing the numbers one to twenty five and the player searches for the numbers in ascending order while the application evaluates his/her attention level. Mind Hunter, MindBlaster, and Focus Pocus all focus on enhancing the players' level of attentiveness. Although these educational games exist, none of them had the desired features that were required for this study, as the games primarily focus on developing the attention skills of the player. Consequently, there was a need for this study to develop its own BCI mathematics educational game (Math-Mind game) that incorporate cognitive functions like inhibitory control, math anxiety, and working memory which, are examined in this dissertation.

2.7. Summary

This chapter provided an overview and history of BCI technologies to familiarize the user with the key device that is used in this study. The functioning of a BCI system, from signal acquisition to controlling an application, was discussed. The different brain signals used for BCI operations were explained along with several uses of a BCI system. This ensures that the reader fully understands the functioning of a BCI so that its application in enhancing educational skills discussed later in the results will be easily comprehensible.

In the next chapter (Chapter three), a thorough literature review on the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) and mathematics educational games will be provided.

CHAPTER THREE

GAMES, COGNITIVE FUNCTIONS, AND MATHEMATICS EDUCATION

3.1. Introduction

This chapter covers a comprehensive literature review on the use of games as a tool for enhancing mathematic skills. The relationship between games and mathematics is clearly established. Also, the chapter presents a review on how selected cognitive functions impact on mathematics. The chapter culminates with how cognitive functions can be integrated in games to facilitate the learning of mathematics. A mind-map of this chapter is presented in Figure 3.1 below for quick recall and reference purposes.

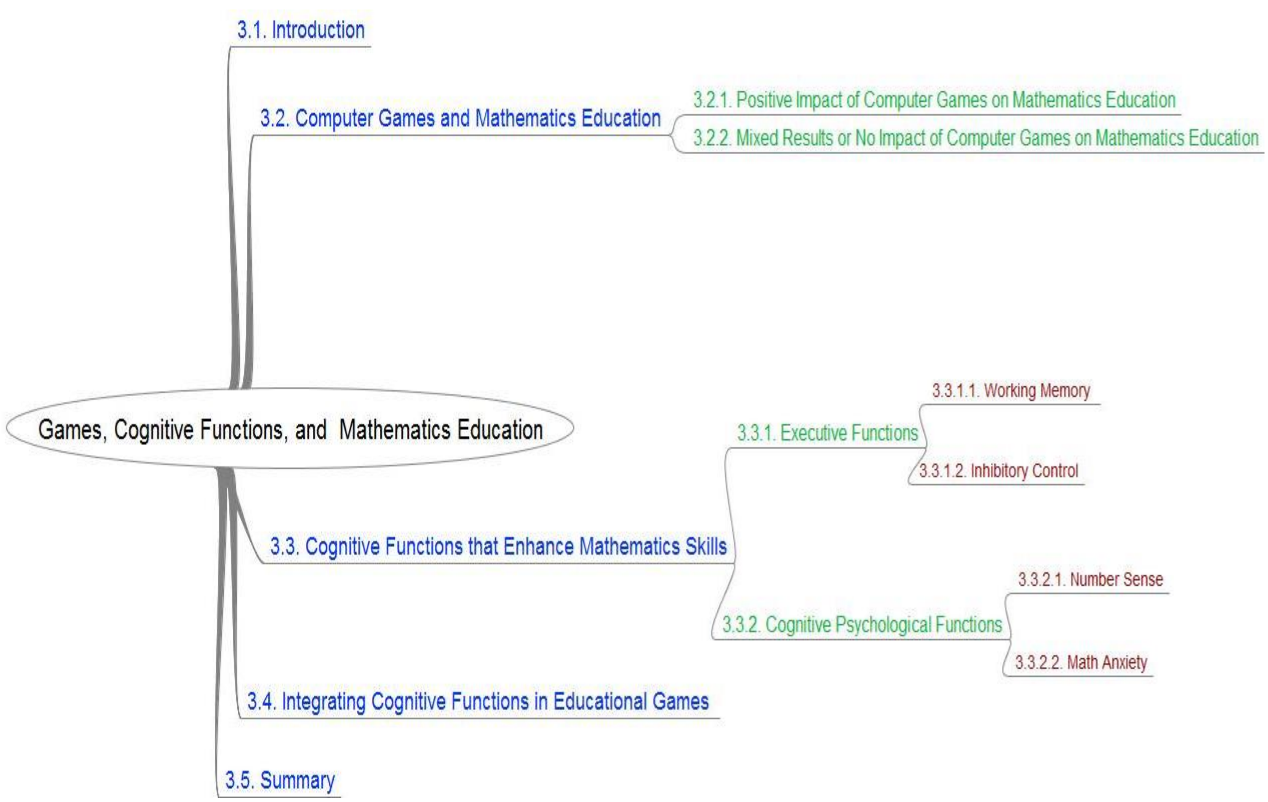

Figure 3.1: Mind-map of Chapter Three

3.2. Computer Games and Mathematics Education

Digital educational games have been widely used over the years as a means for enhancing the mathematics skills of learners. Over the past decade, many researchers and academics have started to pay special attention to the impact that computer games could have on improving mathematics performance in schools (Ke & Grabowski, 2007; Kim & Chang, 2010; Oblinger, 2006). However, many studies have failed to reach consensus on the impact of computer games on mathematics skill development. Some studies (Bokyeong *et al.*, 2009; Burguillo, 2010; Kebritchi *et al.,* 2010; Lopez-Moreto, & Lopez, 2007) have found significant evidence to support the use of computer games for mathematics education, while others (Lim *et al.,* 2006; Nusir *et al.,* 2012; Vos *et al.*, 2011) have had mixed results or no impact.

3.2.1. Positive Impact of Computer Games on Mathematics Education

Computer games have been recognized as important tools for mathematics education because they provide an effective and fun learning environment (Oblinger, 2006). After examining the effects of gameplay on fifth graders in the Unites States, Ke and Grabowski (2007) established that gameplay had a significant positive effect on the students' mathematics performance and attitudes towards mathematics. These researchers used a pre-test/post-test experimental research design with two groups of students (one group being the game playing group and the other the non-game playing group). The findings indicated a significant improvement in the mathematics attainment of the game-playing group compared to the non-game playing group. Likewise, Moreno (2002) found that mathematics educational games had a positive impact on mathematics skills. The researcher used an interactive multimedia game to help elementary school children in learning how to add and subtract integers. The study established that the use of the game significantly facilitated the understanding of these basic mathematics concepts. Another study that showed the positive impact of games on mathematics education was carried out by Young-Loveridge (2006) in New Zealand. The study used 106 participants who represented the bottom performing students in a numeracy test. Of these participants, 23 were put on a program for playing games as a means of learning mathematics skills, while the remaining 83 served as a control group. The findings indicated a significantly high gain of mathematics abilities in the children attending the program compared to the control group.

More recent studies (Bragg, 2012; Burguillo, 2010; Chun-Yi & Ming-Puu, 2009; Delacruz, 2011; Kebritchi *et al.*, 2010; Shin, Sutherland, Norris, Soloway, 2012) within the past five years have also established the positive impact that mathematics educational games have on the development of mathematics skills. Shin *et al.* (2012) carried two different quasi-experiments with two groups of participants (41 and 50 respectively) comprising of second graders in the United States. Both experiments showed that computer mathematics games significantly increased the mathematics skills of the students. Delacruz (2011), using a sample of 164 fourth to sixth grade students in Los Angeles, uncovered that after playing mathematics educational games, the experiment students recorded a significant increase in their post-test scores compared to the pre-test scores. Abdullah *et al.*, (2012), focusing on primary school children in Malaysia, divided students into two groups to study multiplication. One group was taught using the conventional way and the other group was taught using both the conventional way supplemented by multiplication video games. The results of the study revealed a significant positive effect on the students' retention and mastery of multiplication tables for the students who used the multiplication game compared to those who relied solely on the conventional classroom instructions. Furthermore, Bragg (2012), using four treatment groups in three schools, established that mathematics games significantly enhanced students' attitudes towards mathematics, as well as their mathematics performance. This was, however, not the case with the control group. Although mathematics educational games have been seen to significantly improve the mathematics skills of most children, some studies have also found otherwise.

3.2.2. Mixed Results or No Impact of Computer Games on Mathematics Education

Kim and Chang (2010) in their study based on a sample of 170,000 English speaking fourth graders who played mathematics computer games in school every day, found that they had a significantly lower level of mathematics attainment than those who did not. These authors suggested that the daily games could have served as a possible distraction for the student's engagement in school work. Conversely, the researchers also found that for the minority non-English speaking students, playing games every day had a significant positive impact on their mathematics skills. Çankaya and Karamete (2009) carried out a study with 176 students from two primary schools in Turkey and did not find any significant relationship between mathematics educational games and mathematics attainment. The researchers, however, acknowledged the need for further studies in the domain since there was very limited research on the impact of games on mathematics that focused on games developed in Turkey. Lim *et al.* (2006), using a series of primary school children of age from 10 and 11 years, administered a 3D educational game known as Quest Atlantis to determine if it had a positive impact on their science lessons (mathematics included). The study found that although the post-test scores increased for some science lessons, there was a generally low level of engagement, which possibly resulted from issues such as distractions in the game and lack of computer competence in completing the game tasks. It is, therefore, important for educational game designers and developers to take into consideration the target audience and create games with minimal or no usability issues that can distract the users.

3.3. Cognitive Functions that Enhance Mathematics Skills

Several studies (Blair & Razza, 2007; Bull & Scerif, 2001; Espy, *et al.*, 2004; Libertus & Brannon, 2009; Gilmore *et al.*, 2013) have elucidated that most aspects of mathematics skills are related to cognitive functions. Research in neuroscience has looked at the cognitive processes referred to as executive functions, which have positive impacts on the development of mathematics and reading skills in children. Empirical evidence (Abolmaali & Memari, 2013; Alloway & Passolunghi, 2011; Bull and Scerif, 2001; Espy *et al.*, 2004; Oberle & Reichl, 2013) indicate a significant positive relationships between executive functions and early mathematics ability in young children. Similarly, cognitive neuropsychology has revealed that factors such as number sense and math anxiety are important aspects of mathematical competence (Libertus and Brannon, 2009; National Mathematics Advisory Panel, 2008).

This study will focus on the executive functions and cognitive neuropsychological functions that have been established to have a significant relationship with mathematics aptitude. The outline of this section is depicted in Figure 3.2 below.

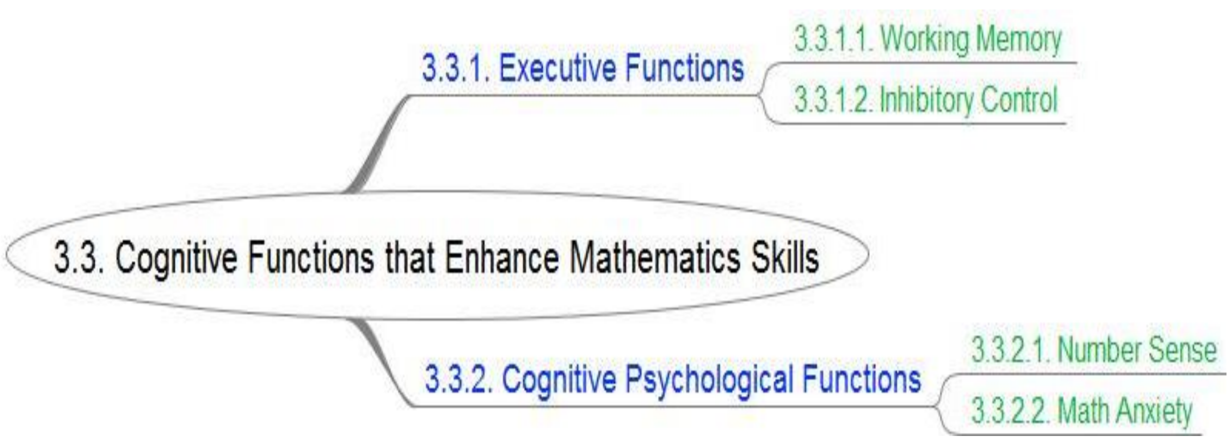

Figure 3.2: Overview of Selected Cognitive Functions that Enhance Mathematics Skills

3.3.1. Executive Functions

Executive functions refer to the shifting of awareness, working memory, and inhibitory control of cognitive processes that are used in problem solving and goal oriented activities (Blair & Razza, 2007). A number of studies (Barrouillet & Lépine, 2005; Blair & Razza, 2007; Bull & Scerif, 2001; Clair-Thompson & Gathercole, 2006; D'Amico & Guarnera, 2005; Espy *et al.*, 2004; Geary, Hoard, Nugent, & Byrd-Craven, 2008; Van der Sluis, De Jong & Van der Leij, 2007) in neuroscience and neuropsychology have examined the relationship between executive functions and mathematics. Bull and Scerif (2001) noted that all measures of executive functions, except for dual-task performance, were significantly correlated to mathematical ability. The study elucidated that children with a high level of executive functioning had superior mathematics abilities.

Espy *et al.* (2004) identified that working memory and inhibitory control were highly related to emergent mathematics proficiency in children. Similarly, Blair and Razza (2007) found that the inhibitory control characteristic of executive functions was noticeably highly correlated to mathematics and reading aptitude. Clair-Thompson and Gathercole (2006), in their study on "Executive functions and achievements in school", identified working memory to have a positive impact on the mathematical ability of children. Bull (2008) elucidated that executive functions and number sense provided children with the bases of understanding mathematics which they maintain over their first three years of primary school.

The Math-Mind BCI game used in the study for this dissertation incorporates the concepts of working memory and inhibitory control. These two paradigms are the fundamental aspects of executive functions that have been empirically proven to have the most impact on mathematics aptitude.

3.3.1.1. Working Memory

The first executive function explained here is the concept of working memory (see Figure 3.2). Over the past two decades, there has been substantial empirical evidence depicting the vital role of working memory in enhancing mathematical cognition. Witt (2011) defines working memory as a multifaceted cognitive system that is in charge of storing and processing information in the short-term. Working memory has also been defined as a mental workspace that is responsible for controlling, regulating, and actively maintaining relevant information to accomplish complex cognitive tasks such as mathematical processing (Raghubar, Barnes & Hecht, 2010). According to Fougnie (2008), the ability to perform certain complex tasks (e.g. mathematical processing) highly depends on the capacity to retain task-relevant information in an accessible state over time (working memory) and to selectively process information in the environment (attention). This indicates that the impact of working memory on mathematics aptitude is mostly felt when there is a significant level of attention.

Several studies (Baddeley 2003; Bleckley, Durso, Crutchfield, Engle, & Khanna, 2003; Conway, Cowan, & Bunting, 2001; McElree, 2006; Jonides, Lewis, Nee, Lustig, Berman & Moore., 2008) have highlighted a close relationship between working memory and attention. Other studies (Cowan, 2010; Kane, Conway, Miura & Colflesh, 2007) have even gone further to clarify that limits in the capacity of working memory can be considered as limits in the capacity of attention. Furthermore, brain imaging studies have indicated that spatial working memory and spatial attention are extremely similar such that spatial working memory can be considered as a type of reflective spatial attention (Bengson & Mangun, 2011). It is, therefore, not surprising that many authors have used the terms working memory and attention interchangeable (Chun, 2011; Gazzaley & Nobre, 2013; Miyake & Shah, 1999), with others even remarking that working memory can be better constructed as "working attention" (Baddeley, 1993).

The existing evidence suggesting that working memory and attention overlap (Fougnie, 2008; Lui & Tannock, 2007; Schweizer & Moosbrugger, 2004), have also been used to explain the great role attention plays in the development of mathematics skills (Fuchs *et al.* 2006; Martinussen & Tannock, 2006). The impact of working memory on mathematics aptitude in this study takes into account the role of attention in ensuring the selective processing of the information stored in the memory. This relationship is also of the utmost importance in this study because BCIs have been designed to effectively and efficiently measure attention levels. At this stage, it is important to examine the relationship between working memory and mathematics performance to indicate the importance of developing working memory as a basis for enhancing mathematics performance.

- ***Relationship between Working Memory and Mathematics Performance***

According to Holmes, Adams and Hamilton (2008), the strong relationship between working memory and mathematics skills in children have been consistent across different studies. Numerous studies (Alloway & Alloway, 2010; Kroesbergen, Van de Rijt & Van Luit, 2011; Swanson & Jerman, 2006; Toll, Van der Ven, Kroesbergen & Van Luit, 2011; Witt, 2011) have looked at the relationship between working memory and several measures of mathematics skills. After a comprehensive meta-analysis, Friso-van den Bos, van der Ven, Kroesbergen and van Luit (2013) established that there was a significant relationship between working memory and mathematics. This relationship ranges from lower level numeracy skills to higher level university mathematics. Tolar, Lederberg and Fletcher (2009) established that working memory had a significant effect on arithmetic skills and students' achievement in college algebra. In a study with 128 student participants in Finland aged 15 and 16 years, Kyttälä and Lehto (2008) expounded that passive visuospatial working memory was a key predictor of overall mathematics performance.

Although working memory as a whole has been acknowledged as a key determinant of mathematics skills, working memory is actually a broad concept with numerous components. Researchers (Meyer, Salimpoor, Wu, Geary & Menon, 2010; Smedt, Janssen, Bouwens, Verschaffel, Boets, & Ghesquière, 2009) have shown that each of these components has its own effect on mathematics aptitude. In this dissertation, the three component model of working memory by Baddeley (2003) was adopted as the framework for determining how the different working memory components influence mathematics skills. This framework considers working memory to comprise of three components namely: central executive, visuospatial sketchpad, and phonological loop. Figure 3.3 depicts the three component model of working memory by Baddeley (2003).

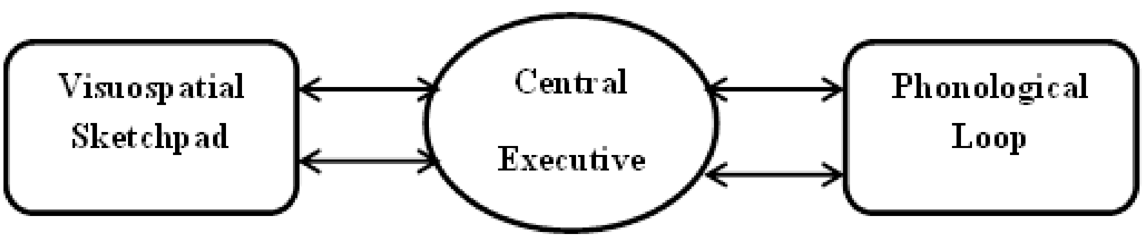

Figure 3.3: Baddeley Three Component Model of Working Memory (Source: Baddeley, 2003)

The central executive is widely considered as the most important component of working memory (Imbo & Vandierendonck, 2008). It is responsible for controlling, regulating, and monitoring cognitive processes (Baddeley, 2003; Smedt *et al.*, 2009). The other two components are considered as subsystems supporting the central executive with temporary storage of information. These two subsystems are also known to be limited in capacity when compared to the central executive. The visuospatial sketchpad is used for the temporary storage of visual and spatial information, while the phonological loop is used for the temporary storage of phonological information. The two subsystems are connected to the central executive and generally referred to as the slave systems of the central executive (Witt, 2011).

The central executive working memory plays a vital role in the development of mathematics skills (Friso-van den Bos *et al.*, 2013). D'Amico and Guarnera (2005) established that children with poor mathematics performance had significant deficits in central executive and visuospatial working memory. Prior studies (Seitz & Schumann-Hengsteler, 2002; Thomas, Zoelch, Seitz-Stein & Schumann-Hengsteler, 2006; Witt,2011) focusing on the mathematics performance of children in addition and multiplication exercises have concluded that the central executive working memory plays a vital role in the completion of these tasks. In support of the role of the central executive in enhancing mathematics skills, Andersson and Lyxell (2007) expounded that children with deficits in central executive working memory had serious difficulties in learning mathematics. This, therefore, indicates that one possible way of improving the mathematics aptitude of children is by enhancing their central executive working memory.

Bachot, Gevers, Fias and Roeyers, (2005) showed that the visuospatial working memory was responsible for solving mathematical problems in which information is represented in spatial form, such as a mental number line. Similarly, Kyttälä *et al.* (2010) indicated that visuospatial working memory was significantly related to mathematics skills and acted as a good predictor of mathematics performance and enhanced the development of mathematics skills. Furthermore, other studies (Clair-Thompson & Gathercole, 2006; Navarro, Aguilar, Alcalde, Ruiz, Marchena & Menacho, 2011) have shown a consistent relationship between visuospatial working memory and mathematics skills. Some of these studies (Kyttälä, 2008; Van der Sluis, Van der Leij & De Jong, 2005) focused on children with working memory deficiency and found that children with deficiencies in visuospatial working memory faced notable difficulties in learning basic mathematics skills. It is also important to indicate here that the impact of visuospatial working memory on mathematics skills is partially determined by age. Prior studies (Andersson & Lyxell, 2007; Kyttälä *et al.*, 2010; Rasmussen & Bisanz, 2005) have shown that the older one gets, the less he/she depends on visuospatial working memory for solving mathematics problems.

The phonological loop has been seen to play a vital role in the retrieval of basic mathematical facts from long term memory (Grube & Barth, 2004; Holmes *et al.*, 2008). People with deficiencies in the phonological loop always find it very difficult to learn mathematics (Andersson & Lyxell, 2007). This relationship has been supported in a study by Friso-van den Bos *et al.* (2013) which indicated a strong relationship between the phonological loop working memory and mathematics skills. Similarly, prior studies (Noël, Seron & Trovarelli, 2004; Smedt *et al.*, 2009) have established that the phonological loop working memory is an important predictor of mathematics aptitude among children in the first and second grades. Furthermore, researchers (Noël *et al.*, 2004; Imbo & Vandierendonck, 2007) have elucidated that the phonological loop is the aspect of working memory responsible for counting and keeping track of operands during calculations.

3.3.1.2. Inhibitory Control

The second executive function explained in this chapter is inhibitory control (see Figure 3.2). Inhibitory control refers to the ability to voluntarily inhibit or regulate strong or automatic attention or behavioural responses. This involves the capacity to focus on relevant stimuli in the presence of irrelevant stimuli, such as attending to teachers' instructions in a noisy classroom. Inhibitory control involves overriding strong but inappropriate behavioural tendencies such as responding to every command even when it is inappropriate to do so (Davis, Bruce, Snyder & Nelson, 2003; Durston, Thomas, Yang, Ulug, Zimmerman & Casey, 2002). One way in which researchers and practitioners in neuropsychology have trained and measured inhibitory control is by using the stop signal task, also known as the Go/No-Go task (Ray Li, Huang, Constable & Sinha, 2006; Sakajiri & Maekawa, 2007; Sylwan, 2004; Verbruggen & Logan, 2008). In the stop signal task the subject presses a button in response to a stimuli. The stop signal task has two stimuli namely: the go signal and the stop signal. When the go signal is presented, the subject is required to perform a given task such as press a button and when the stop signal stimulus is presented, the subject must withhold his/her response during the activity.

Several studies (Clark, Pritchard & Woodward, 2010; Gilmore *et al.,* 2013; Lubin, Vidal, Lanoë, Houdé & Borst, 2013) have highlighted the importance of inhibitory control in learning mathematics. When solving mathematics problems, it is vital for students to be able to identify and inhibit misleading strategies. Clark *et al.* (2010), using a sample 104 children, established that inhibitory control was responsible for mathematics attainment. Walker and Henderson (2012) also showed that high levels of inhibitory control in children were a significant predictor of better mathematics performance in school. Ponitz, McClelland, Matthews and Morrison (2009), after training a group of 343 children in an inhibitory control task, expounded that improvements in the level of inhibitory control predicted gains in mathematics attainment.

3.3.2. Cognitive Psychological Functions

Cognitive psychology is a broad discipline which encompasses how the mind works, perceives information, mentally processes the information, and how the mind calls upon mental resources to make key decisions (Galloti, Fernandes, Fugelsang and Stolz, 2010; Goldstein, 2011). Cognitive psychological functions have been widely established to have a significant influence on education (Laski, Reeves, Ganley & Mitchell, 2013; Newcombe *et al.,* 2009). In this dissertation, two cognitive psychological functions that are known to affect mathematics education will be explained. These two functions are number sense and math anxiety.

3.3.2.1. Number Sense

The first cognitive psychological function explained here is number sense (see Figure 3.2). As indicated earlier, number sense is defined in its simplest form as “the ability to approximate numerical magnitudes” (Siegler, 2009, p. 119). Number sense can also be considered as the conceptual understanding of basic numeration concepts such as counting, using numbers as a representation of a set of objects, and recognizing the number of objects in a set (Jordan *et al.*, 2010; Sousa, 2008). Children always develop number sense capabilities at a very early age; however, these capabilities vary significantly among different children (Klibanoff, Levine, Huttenlocher, Vasilyeva, & Hedges, 2006). According to Jordan, Kaplan, Locuniak and Ramineni (2008), number sense is the basis for developing mathematics skills as well as learning formal mathematic concepts at elementary schools. This is because number sense facilitates the understanding of mathematical concepts as well as enhances problem solving abilities.

A study by Libertus and Brannon (2009) established an important link between number sense (approximate number system) and early mathematics development in children young enough to have had any form of mathematics' training. The finding of this study raises important questions, such as whether a child's number sense can be trained to improve his future mathematic abilities (Libertus and Brannon, 2009). These findings correlate with other studies (Jordan *et al.,* 2010; Van Nes & De Lange, 2007) that also highlighted the significant role of number sense in developing the mathematical abilities of children. It is, therefore, not surprising that many elementary mathematics curricula focus primarily on teaching number sense (Casey, 2004). Many schools have already reaped the benefits of number sense in mathematics education by integrating number sense activities in mathematics classes (Bennison & Goos, 2010; Yang & Wu, 2010).

Research over the years has shown a significant correlation between number sense and mathematics education (Mazzocco, Feigenson & Halberda, 2011; Wilson, Dehaene, Dubois & Fayol, 2009). This relationship has been supported by several studies (Jordan *et al.,* 2008; Maryam, Mahnaz & Hasan, 2011) which showed that the mathematics attainment of children significantly increased after they received training in number sense. Training in number sense alone can result in about 66% increases in mathematics attainment, as shown by Jordan *et al.* (2008). Moreover, a short number sense training period of about 45-60 minutes can significantly enhance the mathematics aptitude of children, as shown by Maryam *et al.* (2011).

The results from the above-stated studies are a clear indication that number sense should be taken seriously when it comes to the development of mathematics skills in children. It is for this reason that researchers (Jordan *et al.,* 2010; Chen, Li & Yang, 2013) have argued that number sense remains one of the most important themes in mathematics education. Likewise, a number of institutions have even developed professional programs for training teachers on how to better understand number sense as a means of improving the mathematics attainment of their students.

One such training program is fully covered in the study by Faulkner and Cain (2013). Findings of their study indicated that training teachers to better understand number sense can have a beneficial impact on the development of their students' number sense. The subsequent effect will then definitely be an improvement in the students' mathematics achievements.

The impact of number sense on mathematics performance is, however, not limited to children. Halberdaa, Lya, Wilmer, Naimana and Germanic (2012), using a sample of over 10,000 people ages 11-85 years, showed that the differences in number sense among people of the same age group related to their differences in school mathematics performance. This relationship was consistent in children, adolescent, and adults.

3.3.2.2. Math Anxiety

The second cognitive psychological function explained here is math anxiety (see Figure 3.2). Ashcraft and Krause (2007, p. 243) define math anxiety as a "feeling of tension, apprehension, or fear that interferes with math performance." According to Zakaria *et al.* (2012) math anxiety is an important physiological dimension of learning that every educator must try to identify in his/her students.

Most students who are weak in mathematics always worry a lot in the process of solving mathematics problems. This aspect of worrying is the key factor that makes them perform poorer (Mohamed & Tarmizi, 2010). Generally, people tend to forget mathematics equations and lose confidence when they are experiencing math anxiety. The findings of most studies (Ashcraft & Krause, 2007; Jansen *et al.,* 2013; Zakaria *et al.,* 2012) have clearly indicated a negative relationship between math anxiety and mathematics performance. As math anxiety increases, the level of math performance decreases. Marsh and Tapia (2002) further indicated that students who have low levels of math anxiety are more confident, excited and more motivated to learn mathematics more than students with high levels of math anxiety. Jansen *et al.* (2013) established that mathematics performance only increases with more practice. This explains why people with high math anxiety tend to perform poorer in mathematics as the anxiety keeps them from solving mathematics problems, as established in Zakaria *et al.* (2012). It is, therefore, of prime importance to identify students with high math anxiety and try to help them build their confidence in solving mathematics problems.

Several studies (Ashcraft & Krause, 2007; Jansen *et al.,* 2013; Ramirez, Gunderson, Levine & Beilock, 2013; Zakaria *et al.*, 2012) have established the impact of math anxiety on mathematics performance. The relationship has been consistent for both '*trait math anxiety'* (Ganley & Vasilyeva, 2011; Miller & Bichsel, 2004) and '*state math anxiety*' (Beilock, Rydell & McConnell, 2007; Brodish & Devine, 2009). Trait math anxiety refers to the general tendency of feeling anxious about mathematics, while state math anxiety is a measure of anxiousness during a mathematics testing situation. In a longitudinal study comprising of 113 grades two and three children, Vukovic, Kieffer, Bailey and Harari, (2013) established that math anxiety was responsible for significant differences in mathematics performance. Ramirez *et al.* (2013), in their study with a sample of 164 grade one and two children, found that there was a negative relationship between math anxiety and mathematics achievement. The relationship showed that children with high levels of math anxiety had poorer mathematics achievements than those with low math anxiety.

Cates and Rhymer (2003) used the Fennema-Sherman Mathematics Anxiety Scale (FSMAS) to classify students according to low and high math anxiety levels and then administered the two groups with a timed mathematics test comprising of basic operations like addition, multiplication, division and subtraction. The findings from the study revealed that students with high math anxiety performed poorer in all the different mathematic operations.

One approach in which math anxiety affects mathematics performance is by interfering with the functioning of the working memory. Vukovic *et al.* (2013) highlighted that mathematics anxiety affected how some students used working memory resources in solving mathematics problems. Ramirez *et al.* (2013) also explicated that math anxiety in first and second graders negatively affected students' working memory resulting in lower mathematics performance.

3.4. Integrating Cognitive Functions in Educational Games

Games generally refer to a form of controlled play. According to Klopfer, Osterweil and Salen (2009), game play comprises of active physical and/or cognitive engagement with the opportunity to experiment, fail, and recuperate. Shute and Ke (2012) note that the number of studies that have examined the development of cognitive processes in games have been substantially low. After examining thirty two empirical studies focusing on using games for learning, Vogel, Vogel, Cannon-Bowers, Bowers, Muse and Wright (2006) concluded that the impact of incorporating games in learning has a significant positive effect on enhancing cognitive functions compared to when using traditional teaching methods without games. With a group of thirty two randomly selected young adults, Nouchi *et al.* (2013) established that commercial brain training games significantly improved their executive functions and working memory. Likewise, Petty and de Souza (2012) using children between seven and eleven years supported the view that games were a vital tool for the training and development of executive functions. Similarly, other studies (Best, 2012; Cain, Landa & Shimamura, 2012; Kasey, Patricia, Naomi, Melissa, & Louis, 2013) have established that video games have a significant positive relationship with executive functions. These findings indicate that video games can be adopted in schools and home settings as a tool for enhancing executive functions.

Garcia, Nussbaum and Preiss (2011) argued that the adoption of serious educational games in schools plays an important role in the development of children's' working memory abilities. This argument was based on their study using 275 grade seven students in Chile. Prins, Dovis, Ponsioen, ten Brink and van der Oord (2011) also indicate that children using a working memory training program that incorporates game components show more motivation and better development of working memory skills than those who do not. Colzato, Wildenberg, Zmigrod and Hommel (2013) showed that first person shooter games were associated with improvements in working memory. The ability to make decisions in gameplay increases a person's critical thinking and problem solving skills which is why games have a significant relationship with working memory. This explains why recent studies (Dye, Green & Bavelier, 2009; Hubert-Wallander, Green, Sugarman & Bavelier, 2011; Karle, Watter & Shedden, 2010; Tanaka *et al.*, 2013) have shown that playing action video games has a superior effect on enhancing visuospatial cognitive skills.

After reviewing the role of selected cognitive functions in the development of mathematics skills, and evaluating how computer games can be used to enhance these cognitive skills, it becomes imperative to bring the two together as a means of contributing to the development of mathematics aptitude. The BCI device provides the ability to monitor and enhance cognitive functions for educational purposes, as suggested by Van Erp *et al.* (2012). However, there is still little empirical evidence to support these suggestions.

Based on the review of selected cognitive functions, a BCI mathematics educational game was developed for the purpose of this study in which empirical analysis were carried out to determine if the BCI could be used to enhance the cognitive skills that play a vital role in mathematics education. For example, math anxiety has been widely established to account for differences in mathematics performance and this math anxiety can be captured in real time by a BCI device using EEG data. Prior cognitive psychological research (Mattarella-Micke, Mateo, Kozak, Foster & Beilock, 2011; Medeiros & Leclercq, 2007; Vukovic, *et al.,* 2013) has measured math anxiety in terms of physiological arousal. In the developed Math-Mind game used in this dissertation, physiological arousal data is captured in real time and on-screen feedback provided to the game player to control and reduce anxiety levels when it becomes too high. This real time neurofeedback approach is an attempt to combine games and BCI technology in training and reducing the level of mathematics anxiety. Similar approaches are also used for enhancing working memory/attention, inhibitory control, and number sense. As previously explained, educational games are selected as the key approach for developing cognitive functions using a BCI because most of the current adoption of low cost commercial off-the-shelf BCIs have been in the gaming industry.

3.5. Summary

This chapter highlighted the relationship between mathematics educational games and mathematics attainment. Studies from different countries were examined. Some studies showed a significant positive relationship while others had mixed or no results. This shows the need to examine the case of South Africa to see if a relationship exists between mathematics educational games and mathematics attainment. Also, the chapter elaborated on how the different cognitive functions impact on mathematics attainment. Lastly, the chapter showed how integrating cognitive skills in games has been useful for developing mathematics skills.

The next chapter (chapter four) provides a detailed explanation of the research design and methodology adopted in this study.

CHAPTER FOUR

RESEARCH DESIGN AND METHODOLOGY

4.1. Introduction

The previous two chapters provided a solid theoretical background on which this study was centred. Relevant aspects of the BCI (as applicable to this study) were reviewed in chapter two and chapter three provided a theoretical review of cognitive functions and their role in the development of mathematics skills.

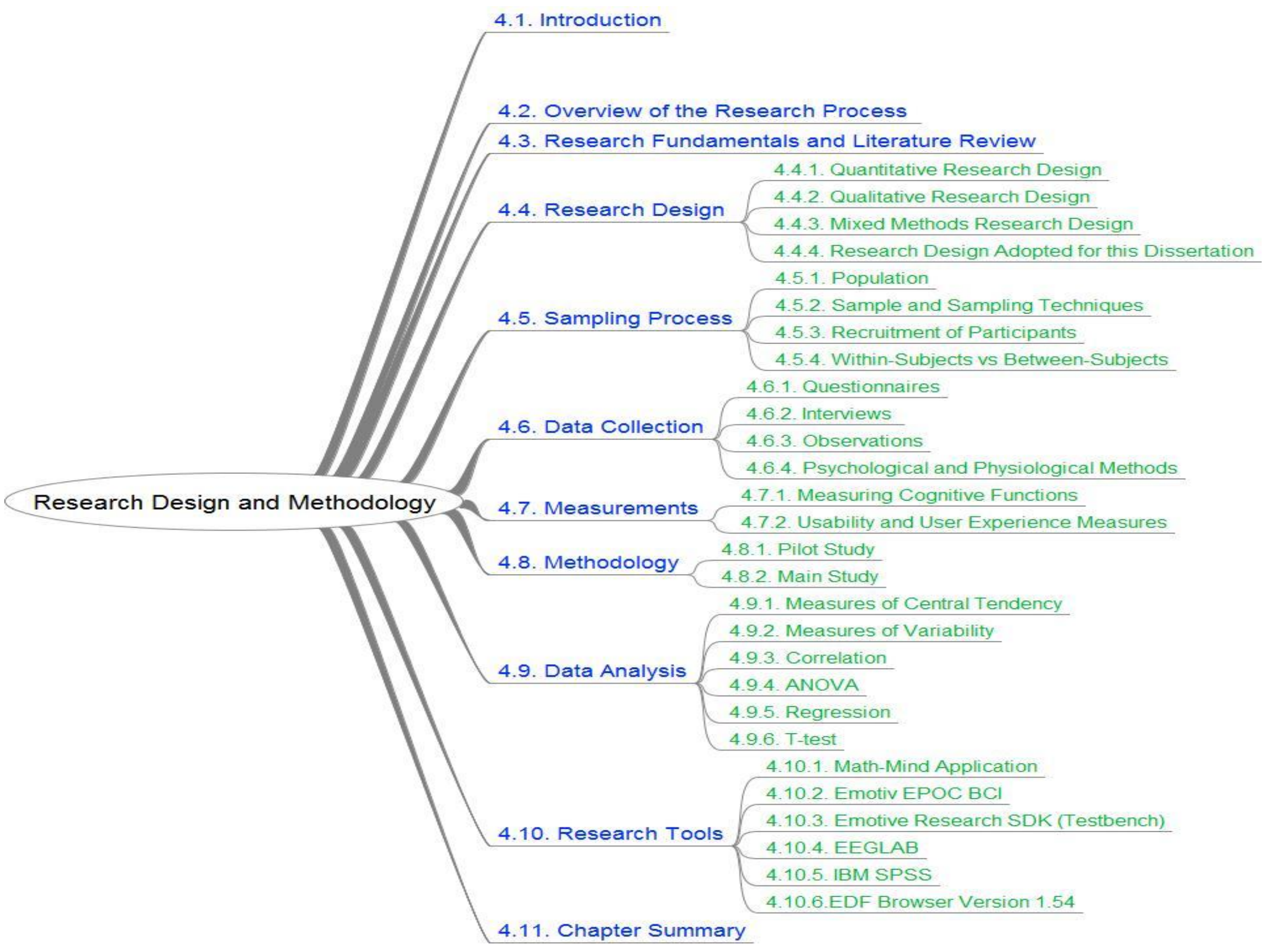

Figure 4.1: Mind-map of Chapter Two

The empirical analysis in this dissertation will be the base for linking the two theoretical chapters in order to provide an understanding of BCI usage for academic purposes with particular emphasis on the cognitive functions that enhance mathematics skills.

This chapter presents and discusses the research design and methodology adopted in this study to answer the research questions and attain the study objectives. The research process followed in this dissertation is clearly articulated with various options for each step indicated, and the selected approach adopted in the study clearly identified. The chapter also discusses how key usability measures and cognitive functions were measured. A mind-map of this chapter is presented in Figure 4.1 above for quick recall and reference purposes.

4.2. Overview of the Research Process

Cooper and Schindler (2003, p. 64) define the research process as "the ordered set of activities focused on the systematic collection of information using accepted methods of analysis as a basis for drawing conclusions." This study adopted a systematic research process (Figure 4.2) in order to successfully attain the objectives of the study. The adopted research process is discussed in detail below. Figure 4.2 below shows the step by step research process followed in this dissertation.

4.3. Research Fundamentals and Literature Review

Research fundamentals represent the core factors that need to be considered before undertaking any research study. These factors include: the research problem, research questions, research objectives, and research hypotheses (Brink *et al.*, 2006; Creswell, 2014; Farrugia, Petrisor, Farrokhyar & Bhand, 2010; Hanson, 2006; Nicholas, 2008; Wood & Ross-Kerr, 2011).

Addressing these research fundamentals established clearly the need for this dissertation as well as what the study intends to achieve.

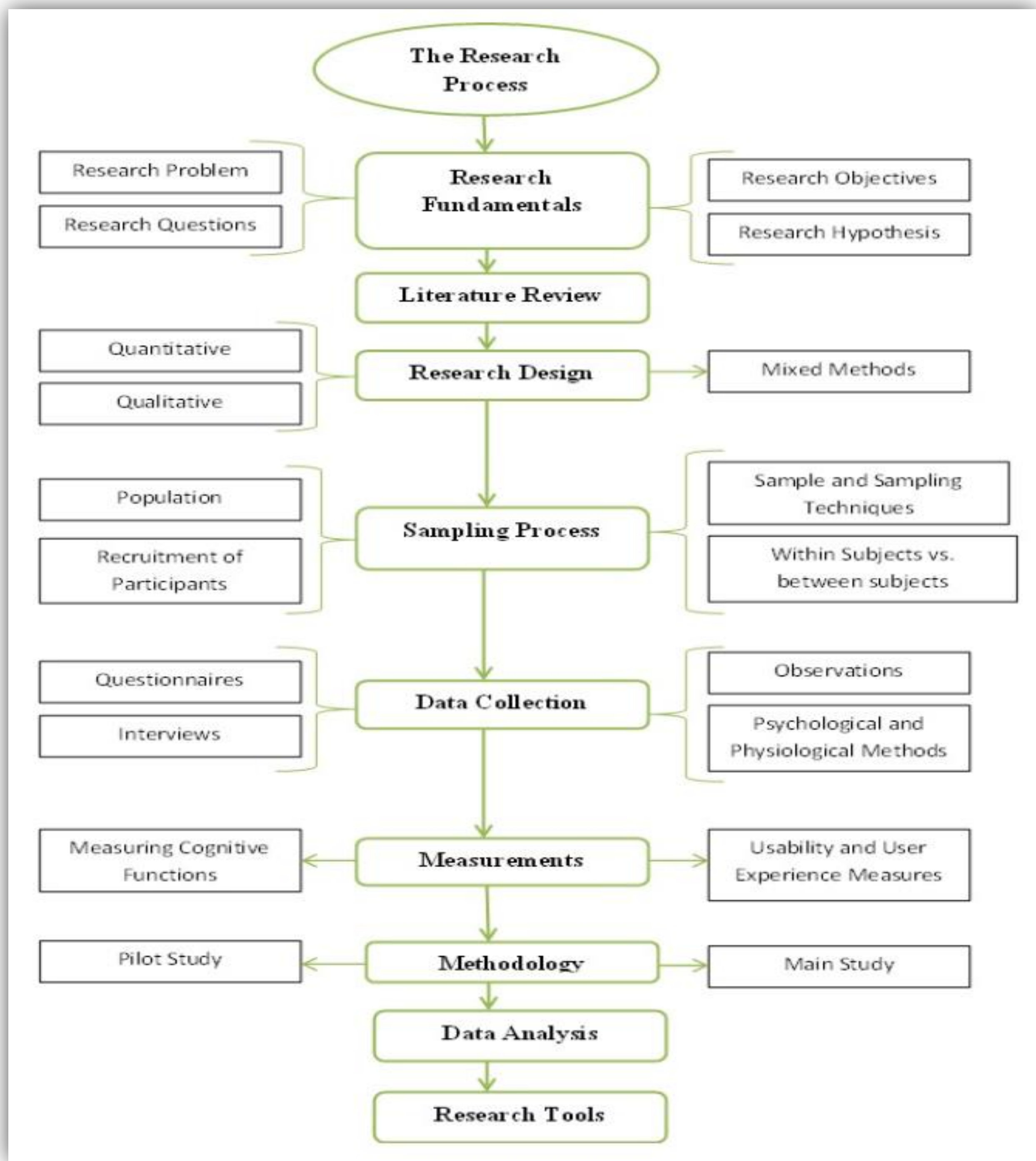

Figure 4.2: The Research Process

As a reference to the research fundamentals in this dissertation, Table 4.1 below depicts the different factors of the research fundamentals and where they were achieved in this study.

Table 4.1: Research Fundamentals

Research Fundamental	Section in which it was covered
Research problem	Section 1.3
Research questions	Section 1.4
Research objectives	Section 1.5
Research hypotheses	Section 1.6

After establishing the research fundamentals, the next logical step as explained by Nicholas (2008) is to thoroughly review existing literature in order to locate similar or related studies that can help the researcher to address the identified research problem. A literature review is an explanation of what accredited scholars and researchers have carried out and published in relation to the research problem/topic under investigation (Nicholas, 2008). Two chapters (chapter 2 and 3) in this dissertation were dedicated to a review of literature that helped to build a deeper understanding of the research problem/topic. Chapter two focused on the BCI device and some domains in which it has been used, such as in medicine, usability, and gaming. Chapter three focused on reviewing existing studies on cognitive functions and how they impact on mathematics aptitude. These two chapters provided sufficient basis to answer the research questions and thus set the foundation for the empirical section of the dissertation.

4.4. Research Design

Welman and Kruger (2000) define research design as the plan explaining how a research study deals with obtaining research participants and collecting information from them. The research design clarifies how the study will deal with participants in order to arrive at a conclusion for the research problem. According to Kirshenblatt-Gimblett (2006), the research design depicts the overall strategy that is selected for integrating the different components of the study in a logical and clear way that ensures effective outcomes for addressing the research problem. Balnaves and Caputi (2001) provide a simplified definition of research design as simply the guideline that explains how the research study was constructed and carried out.

Research designs can be classified under quantitative, qualitative and mixed method research studies (Creswell, 2014). Some research designs (e.g. sequential design) can adopt either a quantitative or a qualitative approach; however, such designs will be discussed only under one of the sections with this characteristic indicated. This is important so as to avoid duplication of facts. Figure 4.3 shows a pictorial representation of the research design.

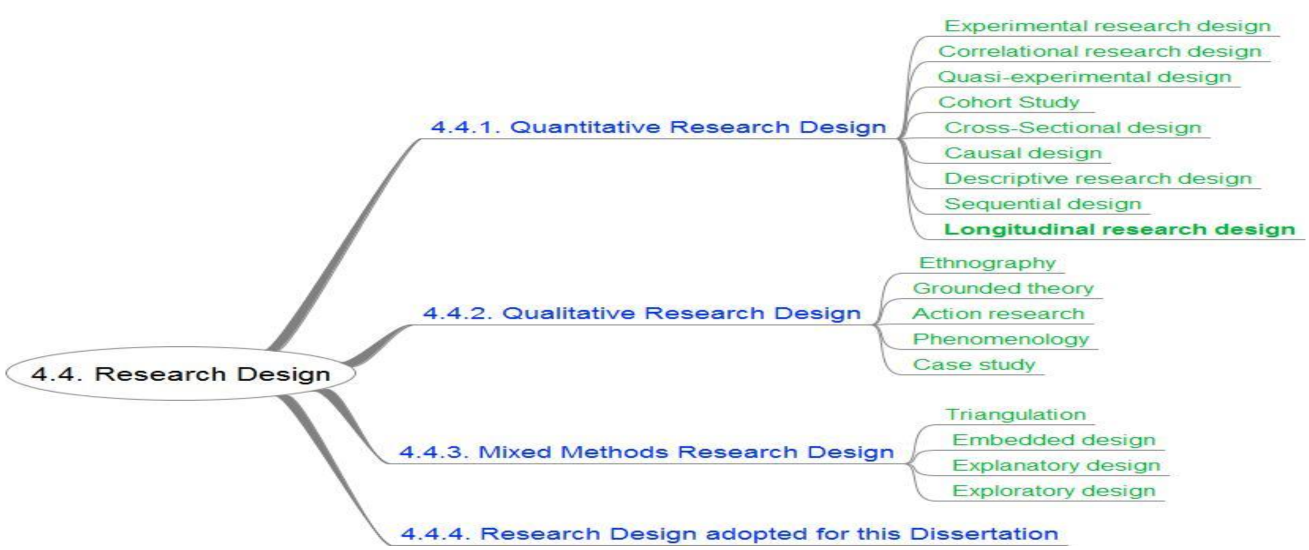

Figure 4.3: Mind-map of the Research Design

4.4.1. Quantitative Research Design

A quantitative research design can be defined as a type of study whose findings are primarily composed of statistical analysis (Ghauri & Gronhaug, 2005). Babbie (2010) shares a similar view by purporting that quantitative studies focus on objective measurements and numerical analysis of collected data with the aim of generalizing the results across groups. Table 4.2 below highlights some of the key characteristics of a quantitative study.

Table 4.2: Characteristics of Quantitative Research

Characteristic	Description
Purpose	➢ To explain and predict (qualities, degree or relation) ➢ To confirm and validate ➢ To test theory ➢ To measure objective facts
Nature of the Study	➢ Focused ➢ Known variable ➢ Established guideline ➢ Static design ➢ Context free ➢ Detached view
Variables	➢ Examines specific variables
Scientific Approach	➢ Confirmatory approach ➢ Testing theories
Data Collection	➢ Standardized instruments (surveys and experimental designs) ➢ Representative, large sample
Reasoning	➢ Mostly deductive analysis

Data analysis	➢ Uses descriptive and inferential statistics to determine statistical relationships
Presentation of findings	➢ Numbers Statistics, aggregated data ➢ Formal voice, scientific style

Source: **(**Schoonraad, 2004; Johnson & Christensen, 2008)

An understanding of the key characteristics of a quantitative study (Table 4.2) is imperative for deciding which type of quantitative research design to follow. Quantitative research designs include: experimental research, descriptive research design, correlational research design, quasi-experimental design, cohort design, cross-sectional design, causal design, longitudinal design, and sequential design. Avison and Pries-Heje (2005) expound that quantitative research designs are the most widely used approaches in investigating information system (IS) research phenomena. This view is supported by evidence from Recker (2013) who used data of published articles in top IS journals and showed that quantitative research was the most common, followed by qualitative research and mixed research designs respectively.

An abridged explanation of the different types of quantitative research methods is presented in Table 4.3 below.

Table 4.3: Quantitative Research Methods

Quantitative Research Method	**Description of method**
Experimental Research Design	❖ Focused primarily on establishing cause and effect (Creswell, 2014; Goddard & Melville, 2007; Welman, Kruger & Mitchell, 2007). ❖ There are three types of experimental research designs, namely: true experiments, double blinded experiments, and factorial experimental designs

Correlational Research Design	❖ A research design in which measurements are made for two or more variables to determine or approximate the degree to which the values for the variables are statistically related (Creswell, 2014).
Quasi-Experimental Design	❖ Nonrandomized, pre-test/post-test intervention studies mostly used when it is not possible to conduct true experiments (Harris *et al.*, 2006; Polit & Beck, 2014). ❖ Experimental research design that does not fulfil all the necessary criteria for controlling surplus variables
Cohort Study	❖ A study conducted over a chosen time period whereby subjects from the selected population are identified and followed-up to determine how their exposure to certain factors affect desired outcomes (Brown, 2009; Bruce, Peat, Mellis & Williams, 2002; Pope & Stanistreet, 2008). ❖ Cohort studies can be classified as prospective or retrospective. ❖ The prospective studies start from the present time and look into the future, while the retrospective studies start from the present time and look into the past to examine events or outcomes (Song & Chung, 2010).
Cross-Sectional Design	❖ A study in which data is gathered at one time period from a representation of the desired population (Mills, Durepos & Wiebe, 2010). ❖ Useful in examining group differences, however, the findings cannot address issues relating to individual cases (Keenan & Evans, 2009).
Causal Design	❖ A study which aims at determining cause and effect by examining whether or not certain variables are responsible for certain behaviours (Singh, 2007). ❖ These studies aim at understanding a situation by means of conditional statements such as “If X, then Y” (Ronet, 2007). ❖ Useful for determining the impact a given change in one variable has on existing assumptions.
Descriptive	❖ A study with a primary focus on determining the frequency of

Research Design		occurrence of something or the extent to which two variables vary (Sreejesh, Mohapatra & Anusree, 2014).
	❖	Primary purpose is to describe the prevailing distribution of variables without any inference to causal relationships (Gromes & Schulz, 2002).
Sequential Design	❖	Subjects are studied repeatedly over a given period of time, usually months or years (Shaffer, 2009).
	❖	Stages of the study are done deliberately, so that one stage is fully completed, before another, and so on, with each stage building on the previous one until sufficient data has been collected to test the hypothesis (Bovaird, & Kevin, 2010; Creswell, 2014).
Longitudinal Research Design	❖	A study in which data is collected from the same sample at two or more different points in time (Todem, 2008).
	❖	Collecting data at two or more different time periods allows for the opportunity to measure change and find possibly explanations for the change (Menard, 2008).
	❖	Also described as a within-subjects non-experimental pretest-posttest in which a single group is studied over a given time period (Gravetter & Forzano, 2012).

4.4.2. Qualitative Research Design

The second type of research design is the qualitative research design. According to Welman *et al.* (2007), a qualitative research design can be best described as an approach instead of a given design or group of techniques. Mason (2002) reveals that qualitative research designs have three common characteristics namely: (1) grounded in the 'interpretivist' paradigm (i.e. the focus is on how the phenomena under consideration are interpreted, experienced, understood, and created or established.); (2) uses research methods that are flexible and sensitive to social context; and (3) based on analytic methods that take account of detail, complexity, and context. Other key attributes of a qualitative research design are presented in Table 4.4 below.

Table 4.4: Characteristics of Qualitative Studies

Characteristic	Description
Purpose	➢ To describe and explain (behaviours and trends or relations) ➢ To explore and interpret ➢ To build theory Construct social reality
Nature	➢ Holistic ➢ Unknown variable ➢ Flexible guideline ➢ Emergent design ➢ Context bound ➢ Personal view
Variables	➢ Focus is always on the entire study and not on specific variables
Scientific Method	➢ Exploratory approach ➢ Focus on the development of new theories and hypotheses.
Data Collection	➢ Observation and interview ➢ Informative, small sample
Reasoning	➢ Usually inductive analysis
Data analysis	➢ Content analysis ➢ Identification of patterns and themes
Presentation of findings	➢ Words Narrative and individual quotes ➢ Personal voice, literary style

Source: **(**Schoonraad, 2004; Johnson & Christensen, 2008)

Qualitative research designs are generally classified into two broad categories namely: interpretive and critical research designs (Cooper & Endacott, 2007). The interpretive types of qualitative research designs include: ethnography, grounded theory, and phenomenology; while the critical qualitative research designs include: action research and feminist research (Cooper & Endacott, 2007). Moreover, a qualitative research design like case study can be interpretive or critical. Because this dissertation does not focus on the above qualitative research designs, an explicit distinction will not be made between the interpretive and critical qualitative research designs. A brief summary of the following qualitative research designs will be provided (ethnography, grounded theory, action research, feminist research, phenomenology, and case study).

An abridged explanation of the different types of qualitative research methods is presented in Table 4.5 below.

Table 4.5: Qualitative Research Methods

Qualitative research method	Description of method
Ethnography	❖ A research approach which focuses on the study of human groups with the aim of understanding how they jointly form and maintain cultural rules (Marshall & Rossman, 2011). ❖ Data is gathered either through overt or covert observation methods (Flick, 2014). ❖ Valuable in IS research for studying IS in organizations (Meyer, 1999).
Grounded Theory	❖ Theory that is inductively developed during a research study and in constant interaction with the data from the study (Maxwell, 2013). ❖ Used in situations where there is little knowledge about the topic under consideration (Bandiera, Lee & Tiberius, 2005). ❖ The final product of a grounded theory research is an analytical product rather than an entirely descriptive account of the analysis (Flick, 2014).
Action Research	❖ Research that "assists in practical problem solving, expands scientific knowledge, enhances actor competencies, is performed collaboratively

		in an immediate situation, uses data feedback in a cyclical process, aims at an increased understanding of a given social situation, is applicable for the understanding of change processes in social systems, and is undertaken within a mutually acceptable ethical framework" (Lau, 1999, p. 149).
	❖	The primary goal of action research is to combine successful real world practical interventions with the development of scientific knowledge (Vries, 2007).
Phenomenology	❖	A study focuses on an in-depth exploration of a phenomenon (Fontana, 2006; O'Brien & Fothergill-Bourbonnais, 2004).
	❖	Effective in expressing the experiences and perceptions of individuals from their own viewpoints (Lester, 1999).
	❖	Widely encouraged in the domain of HCI, participatory design, and design science (Whitaker, 2007).
. Case Study	❖	"An in-depth study of one or more individuals, groups, social settings, or events in the hope of revealing things that are true of all of us" (Jackson, 2012, p. 87).
	❖	Advantages of using case studies in IS research as expressed by prior studies (Detlor, 2004; Myers & Avison, 2002; Recker, 2013) include: (1) the ability to study a contemporary phenomenon on information systems within its natural setting; (2) opportunity to generate theories from practice.

4.4.3. Mixed Methods Research Design

A mixed methods research design combines qualitative and quantitative research methods in the same research study (Tashakkori & Teddlie 2003; Venkatesh, Brown & Bala, 2013). The qualitative and quantitative methods can either be used concurrently (i.e. both methods are independent of each other in the study) or sequentially (i.e. one methods is completed and its findings used as a guide for the other method). Mixed methods research is useful in studies in which either the quantitative or qualitative methods alone cannot fully obtain rich insights into the phenomenon under investigation. The rapidly changing technological landscape often places IS researchers in circumstances where existing theories and findings are insufficient in providing significant insights into the phenomena under investigation (Venkatesh *et al.*, 2013). These researchers argue that the best possible research design for IS researchers in addressing such situations in a way that can make a substantial contribution to theory and practice is the mixed methods research design. Within the context of IS research, some researchers (Tashakkori & Teddlie 2008; Venkatesh *et al.*, 2013) have argued that it is imperative for IS researchers to understand the different purposes of a mixed methods research design before employing it in their studies. A summary of the key purposes of mixed research methods used in IS research studies are presented in Table 4.6 below.

Table 4.6: Purposes of Mixed Methods Research and their Application in IS Research

Purposes of Mixed Methods Research			
Purpose	**Description**	**Prior IS Research**	
		Examples	**Illustration**
Complementarity	Mixed methods are used in order to gain complementary views about the same phenomena or relationships	Soffer and Hader (2007)	A qualitative study was used to gain additional insights on the findings from a quantitative study
Completeness	Mixed methods designs are used to make sure a complete picture of a phenomenon is obtained.	Piccoli and Ives (2003) Hackney *et al.* (2007)	The qualitative data and results provided rich explanations of the findings from the quantitative data and analysis.
Developmental	Questions for one strand emerge from the inferences	Becerra-Fernandez and	A qualitative study was used to develop

	of a previous one (sequential mixed methods), or one strand provides hypotheses to be tested in the next one.	Sabherwal (2001) Ho *et al.* (2003) Grimsley and Meehan (2007)	constructs and hypotheses and a quantitative study was conducted to test the hypotheses.
Expansion	Mixed methods are used in order to explain or expand upon the understanding obtained in a previous strand of a study.	Ang and Slaughter (2001) Koh *et al.* (2004) Keil *et al.* (2007)	The findings from one study (e.g., quantitative) were expanded or elaborated by examining the findings from a different study (e.g., qualitative).
Corroboration/ Confirmation	Mixed methods are used in order to assess the credibility of inferences obtained from one approach (strand).	Bhattacherjee and Premkumar (2004)	A qualitative study was conducted to confirm the findings from a quantitative study.
Compensation	Mixed methods enable compensating for the weaknesses of one approach by using the other.	Dennis and Garfield (2003)	The qualitative analysis compensated for the small sample size in the quantitative study.
Diversity	Mixed methods are used with the hope of obtaining divergent views of the same phenomenon.	Chang (2006)	Qualitative and quantitative studies were conducted to compare perceptions of a phenomenon of interest by two different types of participants.

Source: Venkatesh *et al.* (2013: 26).

Understanding the purpose of a mixed research method is important as it guides a researcher on the type of mixed research method to employ. Creswell and Clark (2011) highlight four main types of mixed research methods, namely: (1) triangulation; (2) embedded; (3) explanatory; and (4) exploratory. These four types are summarized in Table 4.7 below.

Table 4.7: Mixed Research Methods

Mixed Research Method	Description of method
Triangulation	❖ Concurrent combination of qualitative and quantitative methods to understand the same research problem (Venkatesh *et al.*, 2013). ❖ The point at which findings from the qualitative analysis converge with the findings from the quantitative analysis is often considered to represent reality (Yeasmin & Rahman, 2012). ❖ Most widely used mixed method in IS research (Aramo-Immonen, 2013; Recker, 2013).
Embedded Design	❖ Uses either a qualitative or a quantitative method to address research questions within a predominantly quantitative or qualitative study respectively (Creswell, 2012).
Explanatory Design	❖ Uses qualitative data to further explain and gain useful insights into quantitative results that require clarification or further investigation (Creswell, 2012; Creswell & Clark, 2011).
Exploratory Design	❖ Uses quantitative methods to test and explain relationships established in prior qualitative methods (Venkatesh *et al.*, 2013). ❖ Valuable in IS studies because when new technologies emerge, there is often limited existing theories to provide sufficient insights into the scenario under investigation (Venkatesh *et al.*, 2013).

4.4.4. Research Design Adopted for this Dissertation

After reviewing all the above research designs (i.e. quantitative, qualitative, and mixed methods), this dissertation adopted a quantitative research design, specifically a longitudinal research design, as the most appropriate research design for addressing the research problem. As indicated in Table 4.3, in a longitudinal study, data is collected from the same sample at two different points in time. The longitudinal research design has a number of key strengths and weaknesses. Its major strength is the absence of cohort effects as the study examines one group over a given time period as oppose to comparing groups that represent different samples with different characteristics (Gravetter & Forzano, 2012; Kalaian & Kasim, 2008). These researchers also indicate that its key weakness is the extremely time consuming process. Following the selection of a quantitative research design, data collection methods (section 4.6) such as questionnaires and interviews adopted in this study were directed towards gathering quantitative data.

Karapanos, Jain and Hassenzahl (2012) highlight that IS, and specifically HCI researchers, have traditionally viewed longitudinal studies as being too labour-intensive and cumbersome to be of much use in addressing their research problems. However, Karapanos *et al.* (2009) indicated that the study of prolonged use of computer systems is of utmost importance if researchers are to incorporate the changing dynamics and developments in the computing field. Several IS researchers have adopted longitudinal research designs across a wide domain of IS research studies, such as research involving virtual agents (Bickmore & Schulman, 2009; Doering, Veletsianos, & Yerasimou, 2008), BCIs (Combaz *et al.*, 2013; Gates, Hauser, & Sellers, 2011; Nijboer, Birbaumer & Kübler, 2010), technologies for children (Barendregt, Bekker, Bouwhuis, & Baauw, 2006), technologies for health (Kjeldskov, Skov, & Stage, 2010; Klasnja, Consolvo &

Pratt, 2011), awareness systems (Khan, Markopoulos, Eggen & Metaxas, 2010), information virtualization systems (Gerken, Bak & Reiterer, 2007), affective and behavioural computing (Ring, Bickmore & Schulman, 2012), and user experience (Karapanos, *et al.,* 2010; Kujala, Roto, Väänänen-Vainio-Mattila, Karapanos & Sinnelä, 2011), just to list a few.

This dissertation adopted a longitudinal research design as it was deemed to be the most appropriate research design in addressing the formulated research questions and attaining the desired objectives. Participant availability over the duration of time required for a longitudinal research study is always an important issue to consider because the desired results can only be obtained if the participants are available to complete all the required sessions. To address this issue, it is imperative to consider the time frame for which sessions should be planned. It is important to note that in a longitudinal research design, the time factor is not only a characteristic for organizing the study, but also an intra-individual factor that can determine the change process measured in the study (Gerken, 2011). A short period approach was deemed necessary for the purpose of this study, as a longer period would mean the possibility of many external factors affecting the development of the children's cognitive functions. For example, children continuously acquire learning from their daily activities, and this could impact on the development of their cognitive functions.

As briefly mentioned in section 1.7, one way of measuring time in a scientific study is to look at it in terms of the number of data gathering waves (Karapanos, *et al.*, 2009; Singer & Willett, 2003). It is generally acceptable for researchers to implement at least three data gathering waves in order to effectively capture change (Karapanos *et al.*, 2009; Karapanos, *et al.,* 2010; Singer & Willett, 2003). These data gathering waves can either occur within a single session or across different sessions. It should also be noted that longer durations of study and many data gathering waves could yield more comprehensive results. However, Gerken (2011) highlights the cost factor associated with such a study and expounds that researchers should determine whether it is economically viable. Nonetheless, as previously indicated (section 1.7), existing evidence (Combaz *et al.*, 2013; Rieger, 2009) demonstrates that short-term longitudinal studies can effectively capture change. Additionally, Gerken (2011), alludes that the research question of each study should guide the duration and number of data gathering waves.

As such, this study adopted two sessions lasting between 1-2 hours each that had to complete within a week. Each session had two data gathering waves making each subject in the study to undergo a total of four data gathering waves which as indicated by prior studies (Karapanos *et al.*, 2009; Singer & Willett, 2003) will yield sufficient results. Each data gathering wave encompassed the capture of information regarding the subject's cognitive functions. The change process in the level of cognitive functions then addressed the research question of whether the BCI-based mathematics educational game could significantly enhance selected cognitive functions that accounted for mathematics performance in children. The two sessions carried within a one month period was deemed suitable for the purpose of this dissertation after considering factors like participant availability and the cost associated with the study.

4.5. Sampling Process

Nicholas (2008, p. 31) define sampling as "the process of selecting a sample from a population of interest so that the results gained by these participants can be fairly generalized to the population from which they were chosen." In this study, several aspects were considered in order to successfully complete the sampling process. Figure 4.4 below presents a graphical description of the sampling process.

4.5.1. Population

A population in a research study refers to a collection of all individuals with certain attributes that are of interest to the researcher. According to Goddard and Melville (2007), a population can simply be considered as any group that is of interest to the researcher. Research studies are always conducted for the benefit of the population. However, it is not always possible to use an entire population in the study due to its large size. To address this, a sample is then selected from the population and the results from the study are generalized to the entire population. The population for this study comprised of children from the age of 9 and 16 living in the Bloemfontein area in South Africa. Students studying in both urban and rural areas of Bloemfontein were considered for the study. Furthermore, the population comprised of students with a wide background diversity to provide a possible representation of the diversity in South Africa.

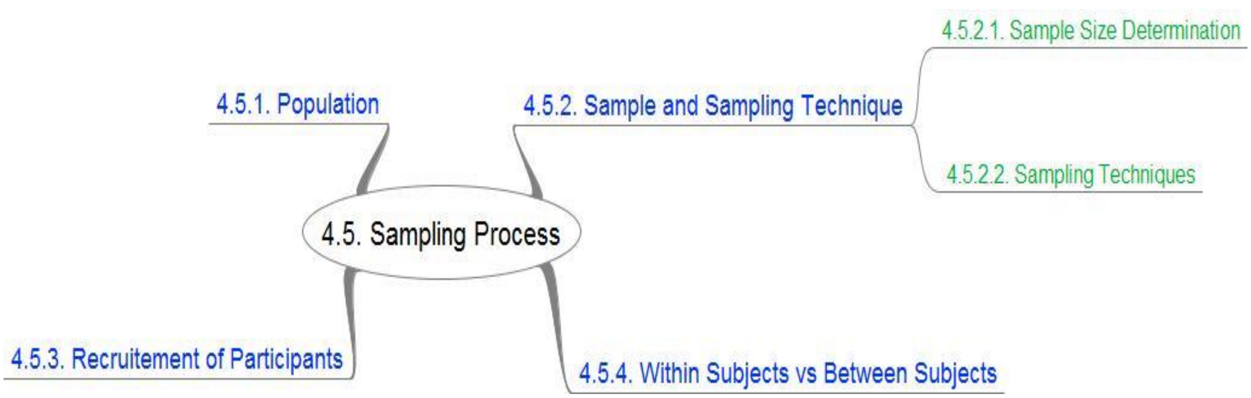

Figure 4.4: Mind-map of the Sampling Process

4.5.2. Sample and Sampling Techniques

Field, Miles and Field (2012, p. 925) define a sample as “a smaller (but hopefully representative) collection of units from a population used to determine truths about that population.” In order to select a sample for a study, the researcher needs to decide on an appropriate sample size and then adopt a sampling technique to use in obtaining the sample. These two aspects are described in detail below.

4.5.2.1. Sample Size Determination

A sample size generally refers to the total number of observations (e.g. participants) to include in a statistical sample. The determination of a sample size in an empirical research study has been noted as a very important but difficult step (Dattalo, 2008; Guo, Logan, Glueck & Muller, 2013; Ryan, 2013). The importance is based on the fact that the sample size can significantly influence the validity of the researcher’s findings as well as its generalization. While, the difficulty emerges from existing academic arguments on which sample size is most appropriate to use.

In 2013, neuroscience researchers (Button *et al.,* 2013; Quinlan, 2013) went heads on in the Nature Reviews Neuroscience journal. Button *et al.* (2013) argued that small sample sizes in neuroscience research resulted in studies with low statistical power and a reduced chance of detecting true effects. In the next issue of the journal, Quinlan (2013) wrote a paper addressing the issue raised by Button *et al.* (2013) by counter arguing that larger sample sizes are not necessarily better, because they hide certain effect sizes that can be easily identified and controlled in smaller samples. A number of neuroscience studies (e.g. Combaz *et al.,* 2013; Iversen, Ghanayim, Kübler, Neumann, Birbaumer & Kaiser, 2008; Müller, Tangermann, Dornhege, Krauledat, Curio & Blankertz, 2008) use sample sizes less than 10 and have been validated in several peer review publications. These arguments are vital in this research because the study of cognitive functions in this study stems from neuroscience and many existing BCI based studies have also adopted the approaches in neuroscience research.

Similar arguments have been seen in the domain of HCI where Tullis and Albert (2008; 2013) present arguments of whether five participants are enough in identifying usability issues. Other IS researchers (Lin, Lucan & Shmueli, 2013; Marshall, Cardon, Poddar & Fontenot, 2013) have also shown that it is not good to have a very large or very small sample as both extremes have known disadvantages. Therefore, it remains the duty of the researcher to justify the selected sample size for each research study and to ensure that such a sample size is appropriate for addressing the desired research questions.

This study adopted a repeated measures approach which does not require a large sample size as highlighted in prior studies (Broota, 2003; Guo *et al.*, 2013; Tullis & Albert, 2008). Nonetheless, it is important to ensure that the sample size is not too small such that it undermines the reliability of the study. To address this problem, this dissertation reviewed BCI-based studies that have adopted a repeated measures approach (i.e. measuring change over at least two sessions) to use as a benchmark for selecting a minimum sample size for this study. The sample sizes of similar BCI studies are presented in Table 4.8 below.

Table 4.8: Sample Sizes of Similar Studies around the World

Authors	**Year**	**Sample Size**	**Type of Study**	**Factor investigated**
Iversen *et al.*	2008	2	Peer review journal article	Cognitive functions in paralyzed patients
Wang & Jung	2011	20	Peer review journal article	Cognitive functions

Ryan	2011	21	MA Dissertation, East Tennessee State University	Enhance target response
Esfahani	2012	10	Ph.D. Dissertation, University of California Riverside	Training the brain to distinguish shapes with a BCI
Kuo	2012	15	Ph.D. dissertation, Louisiana Tech University	Improve cognitive abilities(working memory) and intellectual performance
Areejitkasem	2013	22	MSc. dissertation, University of Wyoming	Visual stimulation for enhancing BCI performance
Thomas *et al.*	2013	5	Peer review conference paper (IEEE)	Attention training for healthy subjects
Lee *et al.*	2013	15	Peer review journal article	Training cognitive skills in the elderly
Combaz *et al.*	2013	7	Peer review journal article	Enhancing Performance

After reviewing the sample sizes of the studies in Table 4.8, it is evident that the sample sizes range from 2 to 22 participants. This clearly supports the view that repeated measures studies need not have very large sample sizes. Looking at the Ph.D. and Masters' dissertations in Table 4.8, the average sample size is 17 participants. Since these dissertations have been validated by the relevant committees in the respective universities, it is plausible to assume that the sample sizes are a reasonable sample size for longitudinal BCI studies. Similarly, in line with prior studies (Kuo, 2012; Areejitkasem, 2013; Leet *et al.*, 2013), a *minimum* sample size of 20 participants was chosen for this dissertation. The actual number of participants that took part in this study is indicated in section 4.5.3 (recruitment of participants).

4.5.2.2. Sampling Techniques

Sample techniques are broadly classified into two major types, namely: probability and non-probability sampling (Lohr, 2010). In probability sampling, some form of randomization mechanism is used for selecting the units to be included in the sample, thus giving each unit in the population some form of probability of being selected (Lohr, 2010). Non-probability sampling, on the other hand, does not encompass any form of random selection. Table 4.9 below provides key points on some of the most commonly used probability and non-probability sampling techniques.

This dissertation adopted a non-probability sampling design with convenience sampling as the primary technique. Convenience sampling was chosen because the study could only use children who were willing to participate and from whom the researcher had obtained the informed consent of their parents or guardians to do so. Convenience sampling was followed by snowball sampling in which the participants could suggest other appropriate subjects for the study so that the researchers could approach them for possible participation.

Table 4.9: Sampling Techniques

Technique	Description	Advantages	Disadvantages
Simple random	Random sample from whole population.	Highly representative if all subjects participate.	Not possible without complete list of population members; potentially uneconomical to achieve; can be disruptive to isolate members from a group; time-scale may be too long, data/sample could change.
Stratified random	Random sample from identifiable	Can ensure that specific groups are	More complex, requires greater effort than simple

	groups (strata), subgroups, etc.	represented, even proportionally, in the sample(s) (e.g., by gender), by selecting individuals from strata list.	random; strata must be carefully defined.
Cluster	Random samples of successive clusters of subjects (e.g., by institution) until small groups are chosen as units.	Possible to select randomly when no single list of population members exists, but local lists do; data collected on groups may avoid introduction of confounding by isolating members.	Clusters in a level must be equivalent and some natural ones are not for essential characteristics (e.g., geographic: numbers equal, but unemployment rates differ).
Stage	Combination of cluster (randomly selecting clusters) and random or stratified random sampling of individuals.	Can make up probability sample by random at stages and within groups; possible to select random sample when population lists are very localized.	Complex, combines limitations of cluster and stratified random sampling.
Purposive	Hand-pick subjects on the basis of specific characteristics.	Ensures balance of group sizes when multiple groups are to be selected.	Samples are not easily defensible as being representative of populations due to potential subjectivity of researcher.
Quota	Select individuals as they come to fill a quota by characteristics proportional to populations.	Ensures selection of adequate numbers of subjects with appropriate characteristics.	Not possible to prove that the sample is representative of designated population.
Snowball	Subjects with desired traits or characteristics give names of further	Possible to include members of groups where no lists or identifiable clusters	No way of knowing whether the sample is representative of the population.

	appropriate subjects.	even exist (e.g., drug abusers, criminals.	
Convenience/Volunteer	Either asking for volunteers or the consequence of not all those selected finally participating, or a set of subjects who just happen to be available.	Inexpensive way of ensuring sufficient numbers of a study.	Can be highly unrepresentative.

Source: Black, (1999:118)

Although convenience sampling is often biased as the units that are easier to select are often not representative of the non-responding units (Lohr, 2010), it has been widely used in BCI studies (Collinger *et al.*, 2013; Combaz *et al.*, 2013; Breshears *et al.*, 2011; Potgieter, 2013; Prueckl & Guger, 2009) due to the difficulty of obtaining a wider and more representative sample. The validation (e.g. peer review publication and dissertations) of the findings in these BCI based studies that employ a convenience sample is an indication of its validity and thus suitable for adoption in this dissertation.

4.5.3. Recruitment of Participants

Parents/guardians of pupils were contacted directly by the researcher to find out if they were interested in allowing their children to participate in the study. For the parents/guardians who allowed their children to participate, the necessary arrangements were made to transport the child to the Laboratory in the Department of Computer Science and Informatics at the University of the Free State (Bloemfontein Campus) where the study was being conducted. A consent form with the accompanying information sheet was provided to the parents/guardians of the potential participant to ensure that they have a full understanding of what was required of their child. The child was then considered a participant of the study after the consent form was signed with full acknowledgment of his/her participation by the parent or guardian. Even after the consent form was signed, the participant still had the overall right to willingly decide whether or not to honour the appointment. Through this process, a total of 36 participants were recruited and took part in this study.

4.5.4. Within-Subjects vs Between-Subjects

Another important factor to consider in research studies is whether the research will follow a within subjects-design or a between-subjects design. This plays a vital role in deciding how participants take part in the study. In a within-subjects study, the focus is on comparing multiple data for each participant, while in a between-subjects study, the focus is on comparing the data from each participant to other participants (Tullis and Albert, 2008; Valente & Sarli, 2011). According to Tullis and Albert (2008) within-subject designs are good when evaluating learnability. A key advantage of the within-subjects approach is that such studies do not require large sample sizes as the researcher should not be concerned about differences among participants (Broota, 2003; Tullis and Albert, 2008). In support of this view, Barrett and Cardello (2012) stipulate that when addressing how independent factors affect cognitive performance, using a within-subjects approach is always preferable as it inherently controls for individual differences. This provided two important points to consider when selecting the approach for this dissertation. Based on these points, the within-subjects approach was chosen for two reasons, namely: (1) obtaining a sample from the representative population to participate in the Lab sessions was very difficult; and (2) since the focus was on cognitive functions, controlling for individual differences was important.

4.6. Data Collection

Data collection is important in a research study as empirical outcomes of the research are based on the analysis of the collected data. Data collection generally refers to the techniques for capturing the data that is vital for addressing the research questions (Perri & Bellamy, 2012). Some of the most commonly used data collection methods include: interviews, questionnaires, and observation. Some types of data that is useful in information systems research, such as behavioural and physiological data, sometimes cannot be captured by these traditional methods of data collection. As such, several automated systems, such as eye-tracking systems and EEG systems have been designed to automatically capture such data during HCI studies or other information system studies. In this dissertation, EEG-based automated data was captured using the Emotiv EPOC BCI device.

4.6.1. Questionnaires

A questionnaire can be defined as "any written instrument that provides respondents with a series of questions or statements to which they are to react either by writing out their answers or selecting from amongst existing answers" (Brown, 2001 p.6). The questions or statements in a questionnaire can adopt either a closed-ended approach or an open-ended approach. Closed-ended questions have predefined responses from which the respondent can select from (Gerber-Nel, Nel & Kotze, 2005), while open-ended questions allow the respondent to provide personal opinions about the things that are important to them. This can be very useful, especially in usability studies (Albert & Tullis, 2013). The questionnaire can be administered by the researcher.

This dissertation made use of questionnaires that were mostly closed-ended, with a few open-ended questions. The open ended-questions were used in the section of usability measures. Albert and Tullis (2013) stipulate that it is important for usability studies to include open-ended questions in addition to other rating scales in order to gain an improved understanding on the user experience. Standardized questionnaires were adopted and modified for use in this dissertation. Modifications included language simplification and reduction of complex items as well as reducing the number of items in the questionnaires to suit the sample population. These questionnaires where used to measure cognitive functions and capture usability measures. The specific questionnaires used are discussed in detail under the measurements they captured (Section 4.7). Pre-test, post-test, and post-session questionnaires were self-administered. The pre-test questionnaire captured the demographic and personal information of the participant, as well as cognitive functions. The post-task and post-test questionnaire focused primarily on the usability aspects of the study and aspects covered during the lab session with the participant.

4.6.2. Interviews

An interview can be broadly described as a dialogue between one or more parties in which one party (the interviewer) elicits information from another party (the interviewee, subject, or participant). Welman *et al.* (2007) classify interviews into three categories namely: structured, unstructured, and semi-structured interviews. With a structured interview, the interviewer follows an interview schedule which is a list of precompiled questions to be asked to the interviewee. The unstructured interviews are informal with no predefined questions and aims to exploit a phenomenon in depth (Welman *et al.*, 2007). The semi-structured interview uses components from both the structured and unstructured approaches.

This dissertation made use of a structured interview. The structured interview followed the same approach as the questionnaire with the only difference being that the interviewer asked the questions and completed the responses on behalf of the interviewee. This was important in the recording of after-task ratings during the lab session as allowing the participant to do it themselves could destabilize the signals of the Emotiv EPOC. Also, since participants were children, this was helpful in reducing the burden of them reading, understanding and answering the questions by themselves.

4.6.3. Observations

Observation is a “way of gathering data by watching behaviour, events, or noting physical characteristics in their natural setting” (Centres for Disease Control and Prevention (CDC), 2008, p.1). Observation is considered to be a scientific data collection method when it addresses an articulated research purpose and is systematically planned and recorded, taking into consideration reliability and validity issues (Kothari, 2004). When carrying out observations, the observer can decide to adopt an overt approach (i.e. the participants know they are being watched) or a covert approach (i.e. participants are unaware that they are being watched). The covert approach can be more beneficial in research studies because participants are likely to act more naturally if they do not know that someone is observing them. One common type of observation method used in IS studies is to observe and measure participants’ overt behaviours (Albert & Tullis, 2013). Observations were used in this dissertation to monitor user behaviour during the tasks.

4.6.4. Psychological and Physiological Methods

Over the years, several instruments have been developed that capture psychological, physiological, and behavioural data from users in real-time. Researchers (Hall, Lockwood & Sheng, 2013; Kenny, 2011; O'Reilly, Woolrich, Behrens, Smith & Johansen-Berg, 2012; Stumpp & Anastasopoulou, 2010) have mostly grouped these tools under the term psycho-physiological measures and they are highly interlinked with regards to the measurements they capture (e.g. stress, anxiety, frustration, etc.). Some of the widely used psycho-physiological measures in IS research studies include: eye tracking systems, EEG-based BCIs, mobile sensors, body postures, galvanic skin response (GSR), inter-heart beat interval (IHBI), and image-based technology. These tools are vital for research purposes because some information such as eye-tracking data and EEG data from BCIs cannot be captured through traditional means (e.g. questionnaires, interviews, or observations).

For the purpose of this dissertation, psycho-physiological data was captured using an EEG-based BCI device (Emotiv EPOC). The Emotiv control panel and research tool were used to capture data on the affective state of the participants as well as EEG scalp recordings during the lab session.

4.7. Measurements

After reviewing the different data collection methods, the next step was to identify the different measurements that were required for attaining the stated research objectives of this dissertation. Identifying the different measures enabled the researcher to allocate the most effective data collection method in capturing the required data. Two groups of measurements were vital for this study (i.e. measurements of cognitive functions, and measurements of usability and user experience). Figure 4.5 provides an illustrative reference for the measurements adopted in this dissertation.

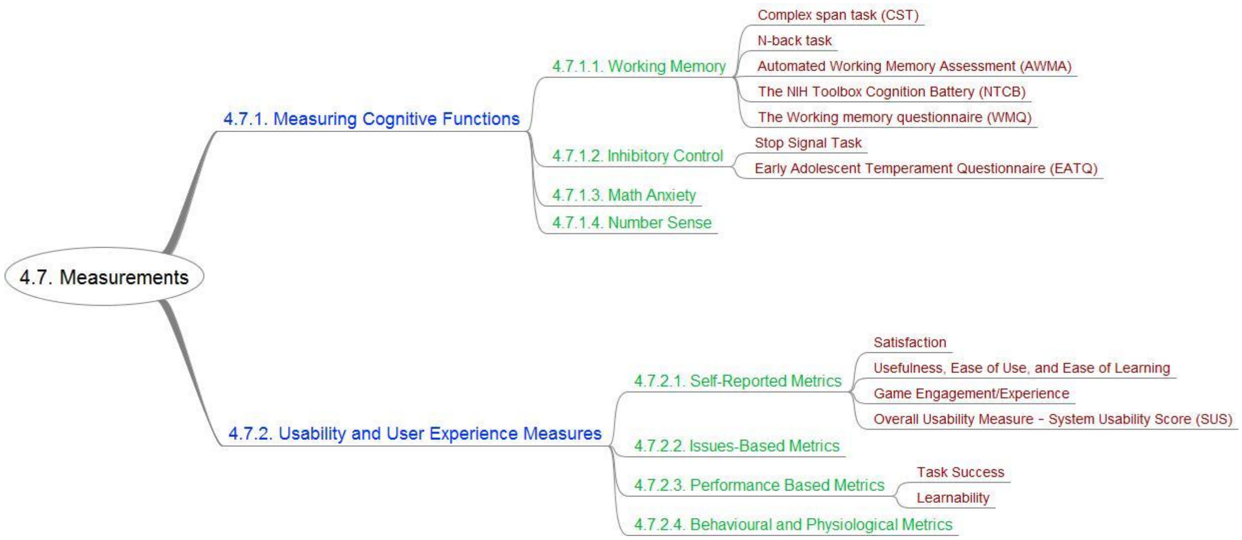

Figure 4.5: Mind-map of Measurements

4.7.1. Measuring Cognitive Functions

Several cognitive functions (e.g. working memory, inhibitory control, number sense, and math anxiety) were the focal point of this dissertation. Over the years, researchers in psychology, neuropsychology, and neuroscience have investigated and developed several tools for measuring cognitive functions. The tools used in measuring each of the cognitive functions in this study are discussed below.

4.7.1.1. Working Memory

Several researchers (Barrouillet, Portrat & Camos, 2011; Conway, Kane, Bunting, Hambrick, Wilhelm, & Engle, 2005; Vallat-Azouvi, Pradat-Diehl & Azouvi, 2012; Wilhelm, Hildebrandt, & Oberauer, 2013) in the field of psychology have investigated and suggested some ways on how to measure the different components of working memory. Some of the most commonly used measures of working memory are: complex span task (CST); n-back task; Automated Working Memory Assessment (AWMA); the National Institutes of Health (NIH) Toolbox Cognition Battery (CB); and the Working memory questionnaire (WMQ). A summary of these tools is provided in Table 4.10 below.

Table 4.10: Tools for Measuring Working Memory

Working Memory Measuring Tool	Description
CST	❖ Participants are required to recall a short stimulus list after a brief retention interval, in combination with the processing of a secondary task (Chein, Moore & Conway, 2011; Schmiedek, Hildebrandt, Lovden, Wilhelm & Lindenberger, 2009).
N-back task	❖ In the N-back task paradigm, subjects are required to observe the identity or location of successive verbal or nonverbal stimuli and to specify when the current stimulus that is presented matches the one shown n-trials before (Owen, McMillan, Laird & Bullmore, 2005; Rudebeck, Bor, Ormond, O'Reilly & Lee, 2012).
AWMA	❖ A standardized tool that can be used by non-expert assessors in measuring working memory (Alloway, 2007b). ❖ The only drawback of the tool is the cost associated with purchasing the licensed copy.
NTCB	❖ NTCB was created to provide a short and efficient computerized test for measuring important neuropsychological functions (working memory included) in children and adult (Akshoomoff *et al.*, 2014; Zelazo *et al.*, 2013).
WMQ	❖ A self-administered scale developed by Vallat-Azouvi *et al.* (2012) for

measuring the three dimensions of working memory.

Of the five different types of measurement for working memory in Table 4.10, the WMQ was found to be the most appropriate for use in this study. Vallat-Azouvi *et al.* (2012) developed the WMQ based on an evaluation of several literature studies on measuring working memory. The WMQ is comprised of 30 questions evenly distributed across the three working memory categories (i.e. 10 questions for each working memory category). The questions are mixed up so that questions focusing on a particular aspect of working memory are not placed in succession. Using a Sample of 382 participants, Vallat-Azouvi *et al.* (2012) confirmed the validity of the questionnaire and found it to have a good level of internal consistency. Concurrent validity of the WMQ was also found with the Rating Scale of Attentional Behaviour and Cognitive Failure Questionnaire which are also tools widely used for measuring cognitive functions, including working memory. Some studies (Carlozzi, Grech & Tulsky, 2013; Vallat-Azouvi, Pradat-Diehl & Azouvi, 2014) have successfully administered the WMQ and found it to provide reliable results. The ease of administration makes it a suitable tool for use in measuring working memory, especially when participants have limited time for lab exercises as the questionnaire can be completed prior to the lab sessions.

4.7.1.2. Inhibitory Control

One way in which researchers and practitioners in neuropsychology have trained and measured inhibitory control is by using the stop signal task, also known as the Go/No-Go task (Ishii-Takahashi *et al.,* 2014). Another important measure of inhibitory control that takes the form of a questionnaire and is widely used in psychology is the Early Adolescent Temperament

Questionnaire (EATQ) (Muris & Meesters, 2009; Whittle *et al.,* 2008). These two methods of measuring inhibitory control were used in this dissertation for the objective and subjective measurements thereof.

- ***Stop Signal Task***

In the stop signal task the participant presses a button in response to a stimuli. The stop signal task has two stimuli namely: the go signal and the stop signal. When the go signal is presented, the participant is required to perform a given task, such as pressing a button. When the stop signal stimulus is presented in turn, the subject must withhold his/her response during the activity.

A similar stop signal task has been adopted for training and measuring inhibitory control with the BCI Math-Mind game used in this dissertation. When a go signal stimulus is presented by the game, the player is allowed to continue playing the game by clicking on the answers in solving the different math problems for killing the alien creatures.

Some of the alien creatures are spawned with a stop signal stimulus which is displayed for some time. Then "go" signal takes over and the stop signal follows again. When this occurs the player has to take care to follow the stop signal tasks. When the stop signal is presented, there is a corresponding cognitive function presented to the player which the player has to invoke from the Emotiv EPOC neuro-headset in order to avoid losing points and player health. If the player invokes the required cognitive action, the player gains points and increases his health status. When the "go" signal is presented, the player can then click on the answers to solve the alien creatures' equation. The player only has the chance to answer the questions when the go signal is presented. Once the stop signal appears again, the player can no more answer the question and can only use the Emotiv EPOC as input to play. This forces the player to invoke various cognitive signals during the stop signal task, thereby learning how to train his/her inhibitory control. Adopting the stop signal task method in the BCI game was useful in capturing objective measures of inhibitory control as the participant engages with the BCI game.

- ***Early Adolescent Temperament Questionnaire (EATQ)***

The EATQ was first developed, tested and validated by Capaldi & Rothbart, (1992). Ellis and Rothbart (2001) later revised the initial EATQ and provided a shortened version known as the Early Adolescent Temperament Questionnaire-Revised (EATQ-R) that has been adopted and used in many studies (Muris & Meesters, 2009; Whittle *et al.*, 2008; Velez, 2010; Stevens, Plumert, Cremer & Kearney, 2012; Vijayakumar, Whittle, Dennison, Yücel, Simmons & Allen, 2014). The EATQ and EATQ-R is comprised of 11 scales of which one measures inhibitory control.

This study only adopted the subscale for measuring inhibitory control from the EATQ-R. The EATQ-R was chosen as a reliable subjective measure for inhibitory control because it has been validated to provide reliable measures for adolescents aged 9-16 years, which is the target population in this dissertation.

4.7.1.3. Math Anxiety

Math anxiety can be measured either using objectives measurements such as physiological arousal (Mattarella-Micke *et al.*, 2011; Medeiros & Leclercq, 2007; Vukovic, Roberts & Green, 2013), or subjective measurements such as the FSMAS (Lim & Chapman, 2013; Zakaria & Nordin, 2008). This dissertation used both objective and subjective measures of math anxiety. The objective measures were obtained by means of EEG similar to Medeiros and Leclercq

(2007), with the main difference being the equipment used. Medeiros and Leclercq (2007) used the BIOPAC system for EEG recordings while this dissertation used the Emotiv EPOC. Physiological arousal was measured by the Emotiv EPOC in terms of instantaneous excitement. The data was captured by the Emotive Control Panel and the BCI Math-Mind application developed by the researcher.

In terms of subjective measures of math anxiety, this dissertation adopted the FSMAS. The FSMAS is a 12 item scale questionnaire developed by Fennema & Sherman (1976). The 12 items follow a Likert scale format from strongly agree (value of 1) to strongly disagree (2) of which six items are positively and six negatively worded. Due to time constraints, the scale was reduced to eight items for the purpose of this dissertation. The sum of responses from the FSMAS is computed to obtain the participant's level of math anxiety. With this scale, a low score indicates a high level of math anxiety and vice versa (Fennema & Sherman, 1976; Zakaria & Nordin, 2008).

4.7.1.4. Number Sense

Number Sense has been widely measured using the Number Sense Test (NST) (Malofeeva, Day, Saco, Young, Ciancio, 2004; Sengul, 2013; Tsao, 2005; Yang, Reys & Reys, 2009). The NST has five components namely: (1) knowing the meaning of size and numbers; (2) knowing the meaning and effect of operation (e.g. addition, subtraction, division, multiplication); (3) understanding and use of equivalent expressions; (4) flexible computing and counting strategies for mental computation; and (5) measurement levels. This study adopted questions from the NST from prior studies (Yang *et al.*, 2009; Tsao, 2005; Sengul, 2013) to develop the NST measure used in this dissertation. A key advantage of the NST is that it has been shown to have a high level of internal consistency for all the measured components (Malofeeva *et al.*, 2004).

4.7.2. Usability and User Experience Measures

Usability and user experience play a vital role in the adoption and use of information systems. Understanding how the usability of an educational application affects brain activity was one of the objectives in this dissertation. To achieve this, several usability and user experience metrics needed to be used to obtain the desired data. Following Tullis and Albert (2013), the different metrics measured in this dissertation are grouped into four broad categories: self-reported metric, issues-based metrics, performance-based metrics (task success, and learnability); and behavioural and physiological metrics (emotions).

4.7.2.1. Self-Reported Metrics

Self-reported metrics are useful in capturing information about users' perception of a system as well as their interaction with it (Tullis & Albert, 2013). The main self-reported metrics used in this dissertation were satisfaction, usefulness and ease of use, and game engagement/experience, and the overall usability measure.

- ***Satisfaction***

According to Tullis and Albert (2013) satisfaction can be broadly viewed as what a user says or thinks about his/her interaction with a system. One way of measuring user satisfaction is through standardized questionnaires such as the Questionnaire for User Interface Satisfaction (QUIS) and the Usefulness, Satisfaction, and Ease of Use questionnaire (USE). Chin, Diehl and Norman (1988) postulate that the QUIS was developed by a team of HCI researchers at the University of Maryland. The QUIS consists of 27 ratings grouped in five categories. The QUIS was adopted in this study because it has been widely used and accepted in many usability studies (Garrett, Horn & Caldwell, 2004; Su, Liu & Lee, 2011; Tullis & Stetson, 2004). Only selected items useful for the purpose of this study were used from the QUIS. The USE was also used to measure satisfaction; however, it is discussed in the subsequent sub-section for usefulness and ease of use

- ***Usefulness, Ease of Use (USE), and Ease of Learning***

Usefulness and ease of use can be measured with the USE which was developed by Lund (2001). The USE is made up of 30 items grouped into four categories of measurement namely: usefulness, satisfaction, ease of use, and ease of learning (Tullis & Albert, 2013). The USE has been widely recognized and used in usability and user experience studies (Akilli, 2005; Hartson, Pyla, 2012; Lund, 2011; Wallace & Yu, 2009). Two to three items were selected from each category of the USE and adapted for the purpose of this dissertation.

- ***Game Engagement/Experience (GEQ)***

User engagement and experience are two important usability aspects in evaluating computer game applications (Schoenau-Fog, 2011). Because this dissertation focused on an educational game, it was important to measure these key aspects. To achieve this goal, the GEQ was selected as the self-reported metric. The GEQ was developed by Brockmyer, Fox, Curtiss, McBroom, Burkhart and Pidruzny (2009), but has since been revised and validated by several studies (Fox & Brockmyer, 2013; Norman, 2013). The GEQ consist of 19 items, however, only 13 items that were suitable for the purpose of this study were selected and used.

- ***Overall Usability Measure – System Usability Score (SUS)***

The SUS is one of the most widely used tools for evaluating the perceived usability of a product (Tullis & Albert, 2013). This tool was developed by John Brooke in 1996 as part of the usability engineering program for Digital Equipment Corporation (Brooke, 1996). The SUS consists of ten items of which the odd-numbered ones are worded positively and the even-numbered items worded negatively. Each of the 10 items is rated on a five point scale from strongly disagree to strongly agree. The answers from each questionnaire are converted into a percentage value to obtain the SUS score. The higher the SUS score, the better the usability of the system. Tullis and Stetson (2004), after evaluating numerous usability questionnaires, concluded that the SUS provided the most reliable results across different samples. The SUS is used in this dissertation to obtain data on the overall usability of the BCI Math game system.

4.7.2.2. Issues-Based Metrics

Tullis and Albert (2013) highlight several usability issues, such as factors that prevent task completion, expression of frustration, not seeing something that needs to be seen, etc. For the purpose of this dissertation, only the frustration aspect of usability issues was addressed. This dissertation used both objective and subjective measures for measuring user frustration. Objective measures of frustration were obtained from the Emotiv EPOC, while the subjective measures were verbally recorded or captured in the questionnaire.

4.7.2.3. Performance-Based Metrics

Performance-based metrics are a valuable tool for usability professionals as they can be extremely useful in determining the magnitude of usability issues. Two performance-based metrics (task success and learnability) were deemed valuable for the purpose of this dissertation.

- ***Task Success***

Task success is the most common usability metrics and can be used in any usability study that has a task (Tullis & Albert, 2013). In order for a participant to be able to complete the usability test in this dissertation, it was imperative to successfully complete the training of the two cognitive functions used in the test first. A participant who could not train the cognitive skills could not participate in the test. Task success is usually measured in terms of binary success or levels of success. This dissertation adopted the binary measure of task success as a participant either succeeded in the task or failed to succeed.

- ***Learnability***

Evaluating the learnability of BCI systems has been an important issue among HCI researchers (Tan & Nijholt, 2010; Zickler *et al.*, 2011). This is because learnability is essential for improving the user performance of such systems. Learnability is vital for the BCI mathematics game because it plays a vital role in determining children's performance in training their cognitive functions. Tullis and Albert (2013) explicate that learning can occur over a short or long period of time. These authors point out that measuring learnability over a long period of time is sometimes difficult to achieve due to availability of participants. As a result, the most practical approach posed by them is to bring in participants over a short time period and acknowledge the limitations of the session. This approach was adopted for this dissertation as participants could only be available for short time periods. There are three alternative approaches to measuring learnability in a short period of time.

The first approach is to perform several trials within the same session. According to Tullis and Albert (2013), this is the easiest approach to administer as participants simply perform a set of tasks without breaks in-between. However, the drawback to this method is that it fails to take into account any significant memory loss. The second approach is to perform several trials within the same session but with breaks in-between each task. Breaks in this session could be implemented in the form of a distracter task that promotes forgetting, however, the key drawback to the method is that the session might become too long (Tullis & Albert, 2013). This is an important issue to consider as participants always become tired during long sessions and might not be collaborative. Some BCI researchers (Combaz *et al.*, 2013) have indicated that sessions were ended when participants became tired. The last approach which is considered the most accurate, although difficult to implement, is to perform trials between sessions. In this approach, the same task is performed over multiple sessions with at least a day in between.

Because of the longitudinal approach adopted in this dissertation, it was possible to follow the third approach which is considered the most accurate in measuring learnability as each participant performed two sessions within a week's period. Following the above-mentioned method, the participants in this study performed the same task over two sessions with at least a day interval between the sessions.

4.7.2.4. Behavioural and Physiological Metrics

Behavioural and physiological metrics usually provide valuable insights into the user experience as it captures things like emotions and eye movements that can help the researchers/usability experts to better understand the participants' interaction with the product. For the purpose of this dissertation, only emotions were necessary to address the researcher questions. It is always important for researchers to understand the emotional states of the participants, as sometimes the views they express on questionnaires as biased. This is because participants sometimes answer what they think the researcher wants to hear (social desirability bias).

The Emotiv EPOC was used to capture data about the emotional state of the participants. The Affectiv Suite of the Emotive EPOC (see section 2.5.2) captured the following emotions: frustration, excitement, engagement, and meditation. The Emotive EPOC BCI system captured

EEG data from the scalp of a user and deciphered the data to obtain the associated emotional states.

4.8. Methodology

This dissertation followed a systematic process using the selected research design as indicated in section 4.4.4. The first step in the methodology was to test the developed research protocol in a pilot study to ensure that all the desired measurements were captured with the selected data capturing tools. The pilot study was followed by two testing sessions. Each of these steps is described below.

4.8.1. Pilot Study

A pilot study is a small scale preliminary study conducted prior to the complete study in order to identify potential biases and address any mistakes that might have been overlooked (Lazar, Heidi & Hochheiser, 2010). The pilot study was carried out to ensure that the selected research tools measured what was expected. Also, it ensured that the questions in the questionnaires were appropriate in bringing out the desired responses. This was achieved by ensuring that vague wordings and errors were identified and corrected before issuing the questionnaires during the session. Three people participated in the pilot session (two for the lab test and one for the questionnaire). The lab session pilot study followed the steps in Figure 4.6 below. The first participant to take part in the pilot study was an adult above the required age for the study. The aim was to identify any possible errors in the system. After the pilot test, several issues were identified and the required changes were effected on the Math-Mind game and the other settings in the testing laboratory.

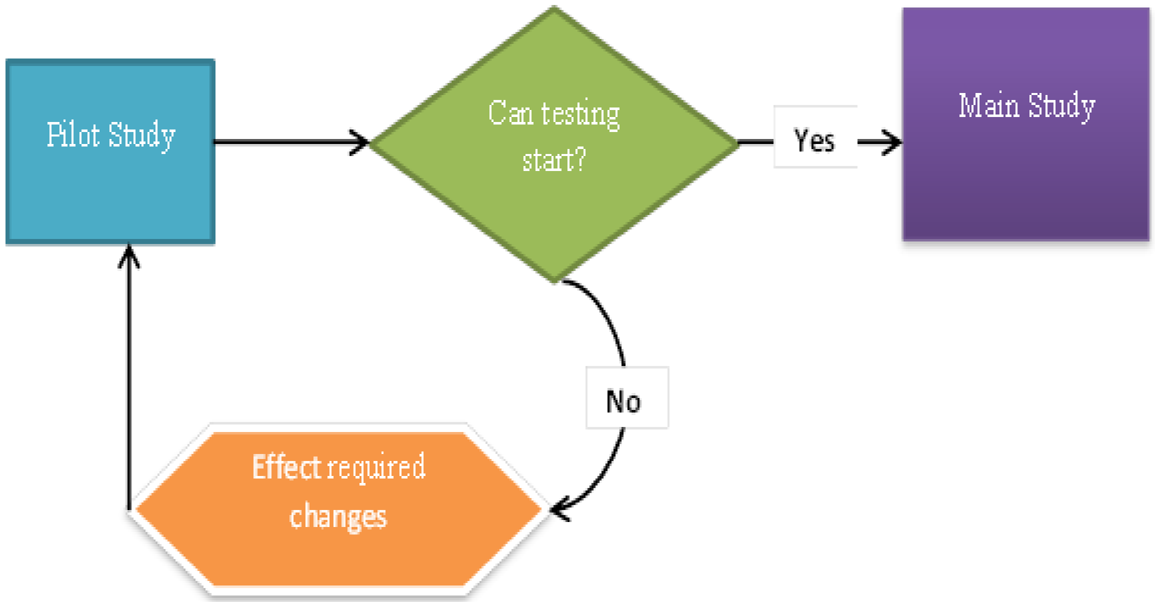

Figure 4.6: Pilot Study

After effecting these changes, the second participant, who was someone in the category of the desired research sample, was brought in for the pilot test. After this test, the final issues were identified and addressed accordingly before it was deemed suitable for the main study to commence. For the questionnaire, a third participant for the pilot study was given the questionnaire to complete and to identify any ambiguous questions or errors. These were then addressed appropriately for the final use in the study.

4.8.2. Main Study

The main study consisted of two sessions. The first session comprised of a short orientation for the benefit of the participant, BCI training, and the first testing for the session. In the second session, only the testing was done as there was no need for repeating the orientation and training. A detailed description of both sessions is presented below.

4.8.2.1. Session One

The following protocol was followed in the first session with the participants.

- ***Part A***: **Welcoming Participant and Training Cognitive Functions with the Emotiv EPOC.**

1. The participant and accompanying parents or guardians (if applicable) were welcomed into the usability laboratory by the researcher. Each of them was offered a place to sit, and then the detail of what was expected from them was explained.
2. The participant and accompanying parents or guardians (if applicable) were taken through the consent form so that they could read and understand the expectations as well as responsibilities of the researcher. The participant and parent/guardian then signed the consent form if he/she was happy and willing to participate in the study. In some cases, the parents/guardians signed the consent form prior to the laboratory sessions during the time they decided to allow their child to participate in the study. The researcher was present at all times to offer any assistance with understanding the content of the consent form.
3. After completing the consent form, the information of the participant was captured into the system as a willing participant of the study.
4. The researcher instructed the participant to sit comfortably so that the Emotiv neuro-headset could be correctly placed on the participant's head.
5. The information of the user was added to the Emotiv Control Panel as a new user and saved. This created the profile for the user in the control panel.
6. The researcher opened the Cognitiv Suite for the training of the cognitive actions. Three cognitive actions were trained namely: Push, Pull, and Neutral.

7. Before commencing with the training of the cognitive actions, the researcher ensured that the Emotiv signals were good (i.e. green color indicators).
8. The researcher then added the Push and Pull actions in addition to the existing Neutral action and trained all three actions with the participant.
9. Each of the actions added were trained in the training section of the Cognitiv Suite.
10. After the training of cognitive actions was complete, the researcher switched to the Affectiv Suite and explained it to the participant. The Affectiv Suite captured the participant's physiological data and did not need to be trained. However, it increased its accuracy over time.
11. The Affectiv Suite was allowed to capture data for about two minutes while the participant sat in a comfortable position. This ensured that the Affectiv Suite captured enough data to obtain reliable physiological measures.
12. After the training was complete, the Emotiv EPOC was switched off in order to save battery power for the next phase of the session.

➢ ***Part B***: Explaining the Details of the Laboratory Exercise

1. The participant played two levels of the Math-Mind BCI game. Each of the levels was played twice in this session resulting in four data gathering waves. Between the two attempts, a distracter exercise that comprised of playing a non-BCI based game was undertaken for five minutes.
2. The details of the game were explained to the participant as indicated below.

2.1.The participant used the BCI in the game to invoke cognitive actions. This activity used the game training of Cognitive functions that lasted for about three minutes (see Figure 4.7 below).

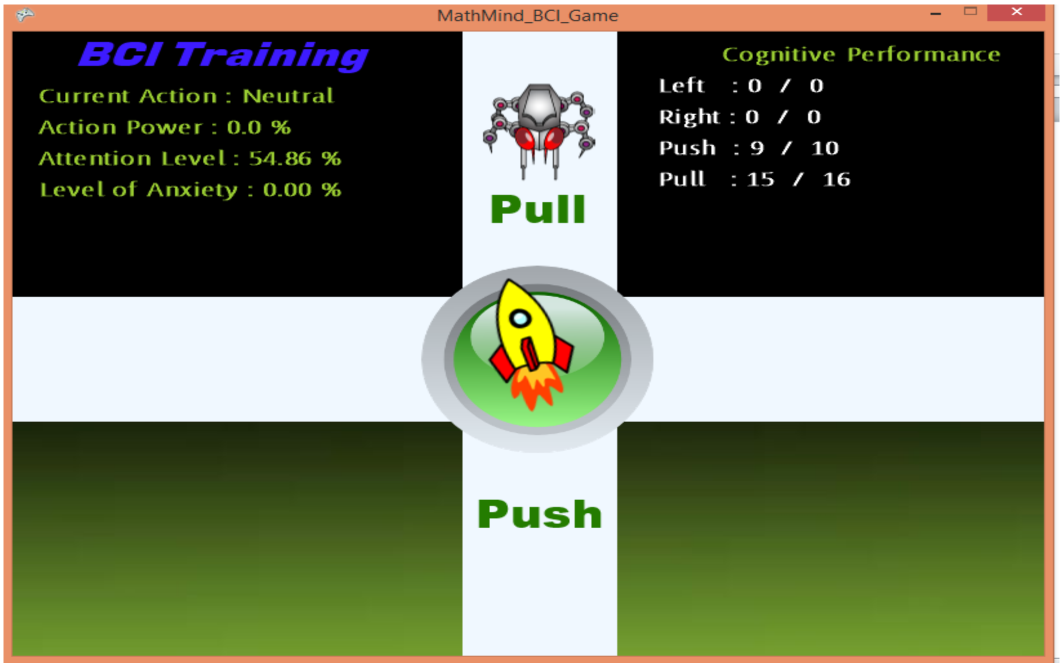

Figure 4.7: Math-Mind BCI Game Training

- Figure 4.7 indicates the two cognitive actions that were used for the purpose of this study (pull and push actions). The other two cognitive functions have been disabled in this version of the game.
- The top left corner depicts the current cognitive action evoked by the participant, the power of the cognitive action, and the level of the participant's anxiety and attention.
- The top right hand corner indicates the performance based on how many times the participant successfully evokes the required cognitive action.
- The participant was instructed to look at the path on which the robot is moving and evoke the cognitive function displayed on the track.

- ❖ If the cognitive function was correctly evoked, a bullet from the central aircraft was shot at the robot to destroy it.
- ❖ If the robot arrived at the position of the aircraft when the required cognitive action had not been evoked, the robot disappeared and a new robot was spawned.
- ❖ The participant played this "in game" training session for three minutes.

2.2.The interface for level one and level five of the main game was the same. The researcher explained the main game interface as depicted in Figure 4.8 below so that the participant could have full comprehension of the features of the game.

- ❖ The participants needed to provide answers to the questions in order to destroy the alien creatures. For example, Figure 4.8 indicates an alien creature with the equation 4 / 1. Four possible answers are provided for each question and the participant needs to select the correct answer to the question.
- ❖ At the top right corner of the screen is the participants' score.

Figure 4.8: Main Game Features

❖ Below the score is the required action. This section indicates the type of cognitive action the player needs to invoke. The required action is indicated in big bold white text with a green bullet to the left. The action shown is Figure 4.8 is “None”, which means the participant is not mandated to invoke any cognitive function at this stage.

❖ Below the required action is the current cognitive action. This indicates the current action from the BCI. The action from the BCI is depicted in white text to differentiate it from the non-evoked actions.

❖ Below the current cognitive action is a gauge that depicts the participant’s attention level.

2.3.Two important things the participants needed to look out for during the game were the inhibitory control task and the anxiety indicator.

❖ The inhibitory control signal is the red circle that shields the alien creature and the equation. In Figure 4.9, when the inhibitory control signal is presented, the participant is required to invoke the Pull signal from the BCI.

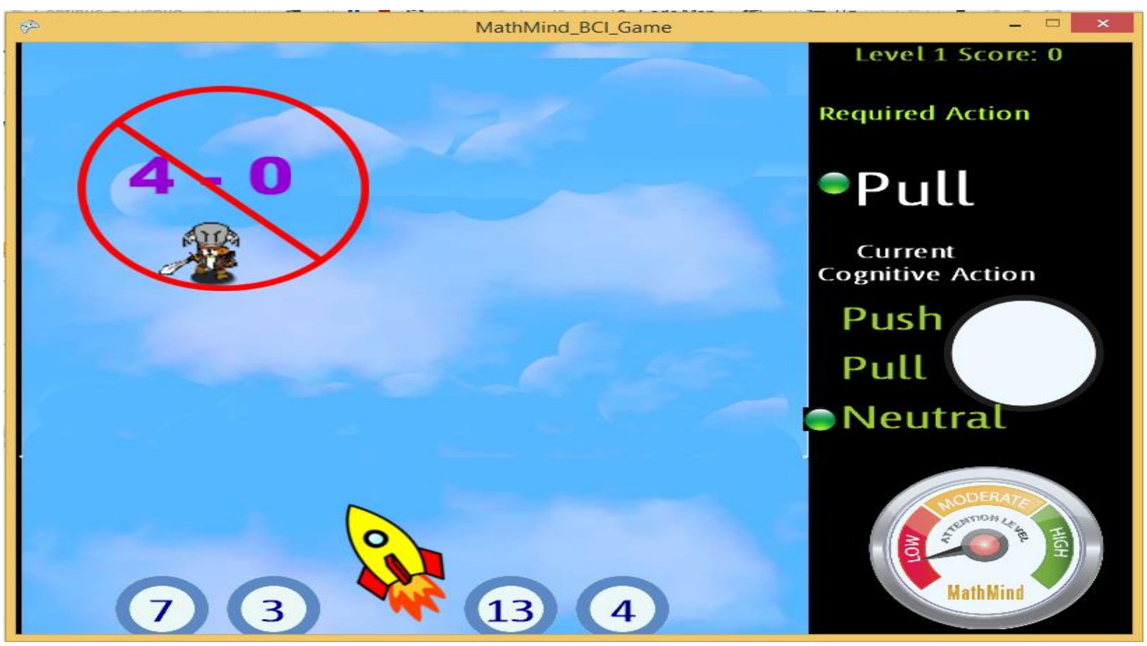

Figure 4.9: Inhibitory Control Features

- The inhibitory control signal (Figure 4.9) will indicate a cognitive function that the participant is mandated to invoke before the signal fades away. During the inhibitory control signal, the answers to the questions were inactive and the participant had to focus on invoking the required cognitive action. When the inhibitory signal disappeared, the participant could then provide an answer to the question.

- When the participant's level of anxiety consistently increased, an anxiety alert (Figure 4.10) was displayed at the top left corner of the screen. This alerted the participant of the high anxiety and encouraged the participant to try and relax. The goal was to aid participants in training how to control and manage anxiety.

Figure 4.10: Math Anxiety Alert

➢ ***Part C:*** **Performing the test exercises in the first session**

The following protocol was followed for the first testing session:

1. The researcher ensured that the participant has brought the pre-test questionnaire which was handed out prior to the session for completion (Appendix C).
2. The different tasks were handed over and explained to the participant.
3. The participant was reassured that all captured information was for the purpose of the study, and will be kept confidential and analyzed anonymously.
4. The Emotiv EPOC headset (which should still be on the participant's head from the training session) was then switched on.
5. If the Emotiv EPOC was removed for convenience during the explanations, the researcher performed step 4 and 5 of section A and then switched on the Emotiv EPOC.
6. The researcher started the Math-Mind application and explained how to play the game and the different components of the game to the participant. This was a recap of the already-explained features, but with an actual demonstration of the game.
7. After the demonstration, a new game was launched for the participant to start playing.
8. The researcher started data capturing immediately when the first task commenced.
9. While the participant was performing the task, the researcher continuously monitored the signals from the Emotiv EPOC using the control panel to ensure that reliable signals were being captured. When a sensor of the Emotiv EPOC did not capture signals (i.e. black color indicator), the researcher repositioned the headset to ensure reliable data capture (i.e. green color indicator).
10. After each task of the session (results of level one and level five of the Math-Mind game), the researcher displayed feedback (Figure 4.11) on the screen and explained the feedback to the

participant. The participant was reassured that the goal of the test was not the actual results of each task but to ensure that he/she beats the results with the next session by following feedback instructions to better train his/her cognitive functions.

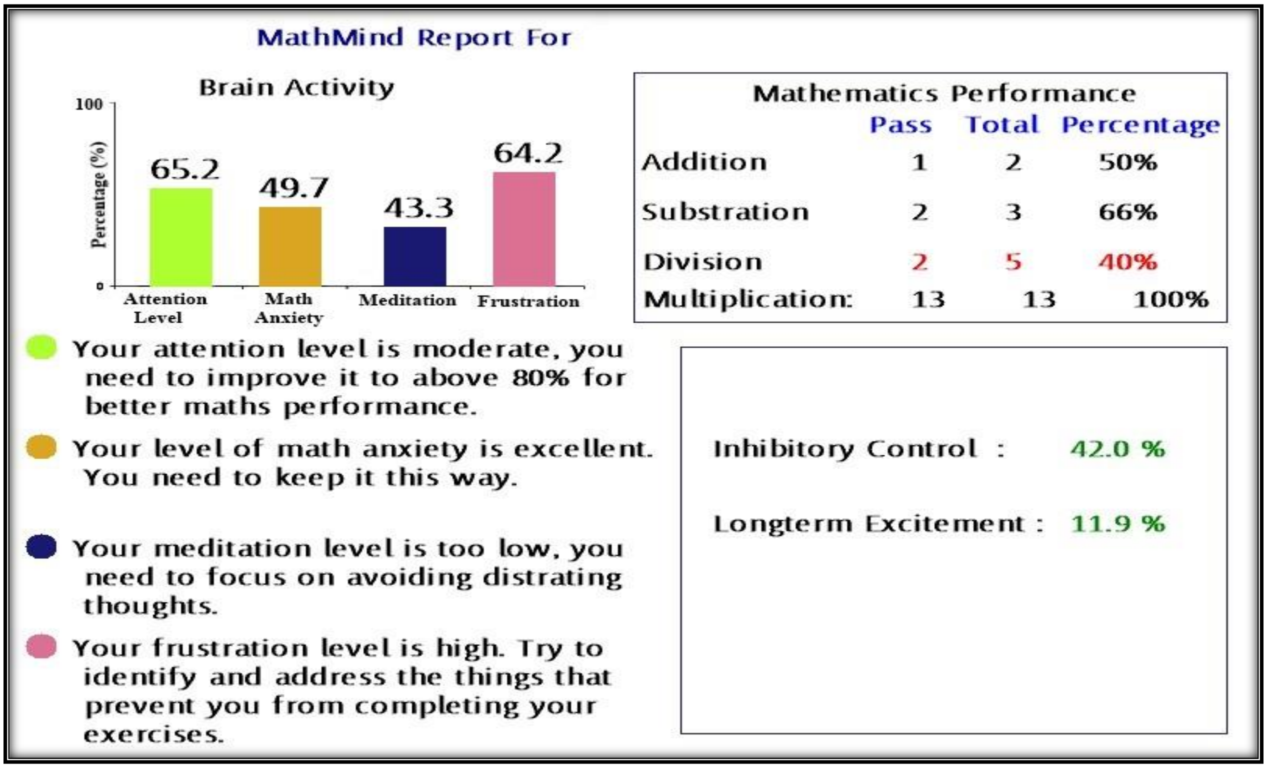

Figure 4.11: Sample Game Feedback

11. During the course of the tasks, the participant could request a break or opt to end the session if the Emotiv EPOC headset made them feel uncomfortable or if they were too tired to continue the session.
12. After completing the different tasks, the researcher ended the session and saved all the data with the participant's unique code.
13. The researcher made an appointment for the second session with the participant.
14. A chocolate bar was handed to the participant as a thank you for participating in the first session, as well as an encouragement to come for the second session.

4.8.2.2. Session Two

The following protocol was followed for the second testing session which occurred on a different day.

1. The session commenced with step one, three, and four of Part A (section 4.8.2.1).
2. Following this was Step 3 - 12 of Part C (section 4.8.2.1).
3. After completing the tasks, the post session questionnaire was handed to the participant for him/her to complete and return to the researcher.
4. An incentive (R50 Kloppers' voucher) was handed to the participant for his/her collaboration in the study.

4.9. Data Analysis

Data analysis comprised both descriptive and inferential statistics. Descriptive statistics places emphasis on describing the data using several measures such as measures of central tendency and measures of variability (Dietz & Kalo, 2009; Tullis & Albert, 2013). Inferential statistics on the other hand are used to identify relationships in a sample that can then be generalised to the wider population (Healey, 2010). Some of the inferential statistical measures used in this dissertation include; correlations, analysis of variance (ANOVA), t-test, and regression.

4.9.1. Measures of Central Tendency

Measures of central tendency describe values that are typical in a dataset (Dietz & Kalo, 2009). This can be achieved by measuring the mean, median and mode. The mean is the average of the dataset which is generally computed by taking the sum of all the values in the dataset and dividing it by the number of values (Tullis & Albert, 2013). The median refers to the middle value in the dataset when the data is arranged in ascending order from the smallest to the highest, while the mode refers to the value that occurs most frequently in the dataset. Means and medians were used in the descriptive section of the analysis.

4.9.2. Measures of Variability

These measures are a reflection of how the data within the dataset are dispersed or spread across the range of values (Tullis & Albert, 2013). Measures of variability include: the range, variance, and standard deviation. The range refers to the distance between the maximum and minimum values in the dataset. The variance indicates how dispersed the data are in the dataset with respect to the mean value of the dataset (Rovai, Baker & Ponton, 2014). The Standard deviation is the square root of the variance and is considered more important in measuring variability than the variance because its values are of the same unit as the original data (Healey, 2010; Tullis & Albert, 2013). Standard deviation was used in explaining variability in the descriptive section of the analysis.

4.9.3. Correlation

A correlation is a statistical analysis method that models a relationship between two or more random variables (Rovai *et al.,* 2014). The strength of the relationship is determined through the correlation coefficient which is a value that ranges from -1 to +1 (Tullis & Albert, 2013). A correlation coefficient closer to -1 or +1 indicates a stronger relationship and coefficient values closer to zero indicate a weak relationship. A negative correlation coefficient indicates a negative relationship and vice versa. Correlation analysis was used in this study to determine relationships between variables (e.g. the relationship between brain activity and cognitive functions).

4.9.4. ANOVA

ANOVA is a parametric test that evaluates whether the mean values of multiple dependent/independent groups are statistically different from each other (Rovai *et al.*, 2014). With ANOVA analysis, a researcher can determine the proportion of variations in the dependent variable that can be attributed to changes in the experimental variables (Rutherford, 2001). ANOVA analysis was used in this study to determine statistically significant differences in cognitive functions across different selected groups.

4.9.5. Regression

Regression analysis is a statistical method that is used in analysing models consisting of one or more independent variables (explanatory or predictive variable) and a dependent variable (response variable). A regression analysis determines how changes in the explanatory variables induce changes in the response variable. A regression analysis can be termed a simple/univariate regression or a multiple/multivariate regression. In a simple regression, only one independent variable is used to explain the dependent variable, while in the multiple regression, more than one independent variable is used to it (McNabb, 2008). Regression analysis was used in this study to determine the impact of affective states and cognitive functions on mathematics.

4.9.6. T-test

A t-test is “a parametric test of differences between two groups’ performance on the same measure” (Stuart-Hamilton, 2007, p. 263). The differences are usually calculated based on the mean values for both groups and then calculating the variations. In this study, two types of t-tests were used namely: the independent sample t-test and the paired sample t-test. Andrew, Pedersen and McEvoy (2011) expounds that the independent sample t-test examines the existence of statistically significant differences between independent groups (e.g. males and females). The paired sample on the other hand compares the means of the same group for a particular measure taken at two different times (Andrew *et al.*, 2011). An Independent sample t-test was used in this study in examining gender differences in cognitive functions, while the paired sample t-test compared measurements of cognitive functions across the different tasks.

4.10. Research Tools

After reviewing the direct measurements and analysis that need to be carried out with the captured data, the next step is to determine the tools that can be used to get the desired measurements and analyse the captured data accordingly.

4.10.1. Math-Mind Application

The Math-Mind application is a BCI-based mathematics educational game that was developed by the researcher. The game incorporates mathematics problems relating to addition, subtraction, division, and multiplication. The Math-Mind game uses an Emostate to decipher the brain signals from the Emotiv EPOC Neuro-headset through the various Emotiv API functions. An Emostate refers to the data structures that contain the current state of the Emotiv EPOC detections, such as the cognitive and affective states.

The game starts by initiating a connection with the Emotiv EPOC. If the connection is successful then the various methods (cognitiv and affectiv)[3] for handling the Emostate events in the game will be called every second to handle the most recent Emostate. The Emostate is then converted into a game function for executing the required task. At the end of the game, the game closes the

[3] Cognitiv and Affectiv methods are generic methods of the Emotiv EPOC system that is used for retrieving cognitive and affective state data from the BCI.

connection with the Emotiv EPOC. Screenshots of the Math-Mind game are shown in Figure 4.6 to Figure 4.10 (Section 4.8.2.).

4.10.2. Emotiv EPOC BCI

Emotiv EPOC is considered as “a high resolution, neuro-signal acquisition and processing wireless neuro-headset” (Emotiv, 2010). The EPOC neuro-headset consists of 16 sensors of which only 14 are standard for data acquisition and processing. The 14 sensors are positioned in accordance with the 10-20 international system. The brain signals decoded by the EPOC neuro-headset are divided into three sections namely: (i) Cognitiv Suite - used to discern the users’ conscious intent; (ii) Affectiv Suite - used for determining emotional states such as excitement, engagement, meditation and frustration; and (iii) Expressiv Suite - used for detecting facial expression.[4] For the purpose of this study, only the affective and cognitive suite measurements were used. The Affectiv suite was used for measuring the usability, while the cognitive suit was used as input for playing the game. Figure 4.12 below shows a screen capture of the Emotiv Affective Suite and the different measures of the affective state are described below the figure.

Engagement: The Emotiv developers define engagement as “alertness and the conscious direction of attention towards task-relevant stimuli” (Emotive, 2010). The Emotiv EPOC headset detects engagement levels by capturing the user’s level of physiological arousal in connection with Beta waves. As mentioned before in section 2.5.1.2, Beta waves refer to the frequency of the human brain activity that ranges from 12-30 HZ. The emotions that relate to engagement are alertness, concentration, interest, stimulation, and vigilance.

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[4] The terms “Cognitiv Suite, Affectiv Suite and Expressive Suite” are the generic names used by the developers of the Emotive EPOC BCI system.

Excitement: This emotion is elicited by stimulation of the sympathetic nervous system which generates a range of physiological responses, such as eye widening, pupil dilation, blood diversion, sweat gland stimulation, heart rate and muscle tension increases, and digestive inhibition. Excitement is categorized into short-term (instantaneous) excitement and long term excitement. Both short-term and long term excitement are measured as an awareness or feeling of physiological arousal. However, they differ in that short-term excitement is tuned to detect changes in excitement over a short period of time (mostly in a few seconds), while long term excitement is tuned to more accurately detect changes in excitement over a longer time period, usually in minutes (Emotive, 2010).

Figure 4.12: Affective Suite of the Emotive Control Panel

Frustration and Meditation: The explanations for the detection of the frustration and meditation emotions by the Emotiv EPOC have not been exclusively explained by the Emotiv developers. However, meditation is depicted as some form of a relaxed state, while usability studies using the Emotiv EPOC have related frustration to an aspect of user experience (Salvador, Legaspi, & Suarez, 2010).

4.10.3. Emotive Research SDK (Testbench)

Testbench is the research tool of the Emotive system which allows the capture of raw EEG data from each of the Emotiv EPOC sensors (Szafir & Signorile, 2011). A screenshot of the Emotiv Testbench is presented in Figure 4.13 below.

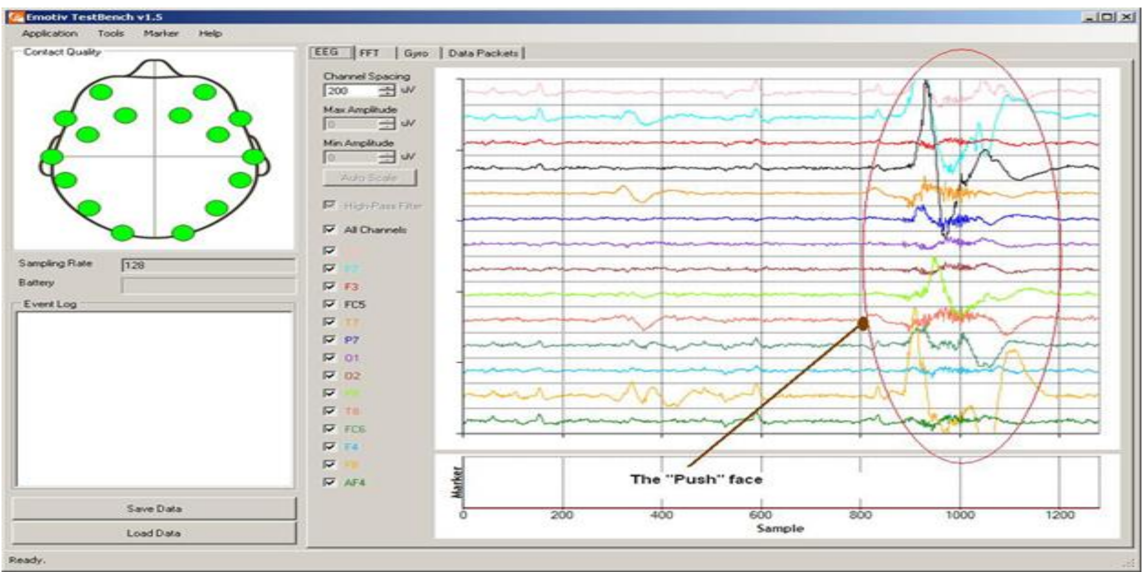


Figure 4.13: Emotiv Testbench

Some of the features of Emotiv Testbench include:

- Real-time display of the Emotiv headset data stream, including EEG, contact quality, fast Fourier transform (FFT)[5], gyro, wireless packet acquisition/loss display, marker events, headset battery level.

[5] The Emotiv EPOC BCI uses FFT to isolate and compute the magnitude of the different brain activities for each of the 14 EEG channels. FFT basically converts time domain-data into frequency-domain data (Du & Swamy, 2010).

- Record and replay files in binary EEGLAB format (Section 4.10.4).
- Covert recorded EEG data to csv format.
- Time markers can be defined and inserted into the data stream and these markers are stored in the EEG data file.
- Export screenshots for documentation.

4.10.4. EEGLAB

EEGLAB (Figure 4.14) is an open source software environment developed by Delorme and Makeig (2004) for analysis and virtualization of brain signals through EEG and MEG data. Some of the key features of EEGLAB include: graphic user interface, multiformat data importing, high-density data scrolling, defined EEG data structure, open source plug-in facility, interactive plotting functions, event and channel location handling, and forward/inverse head/source modelling.

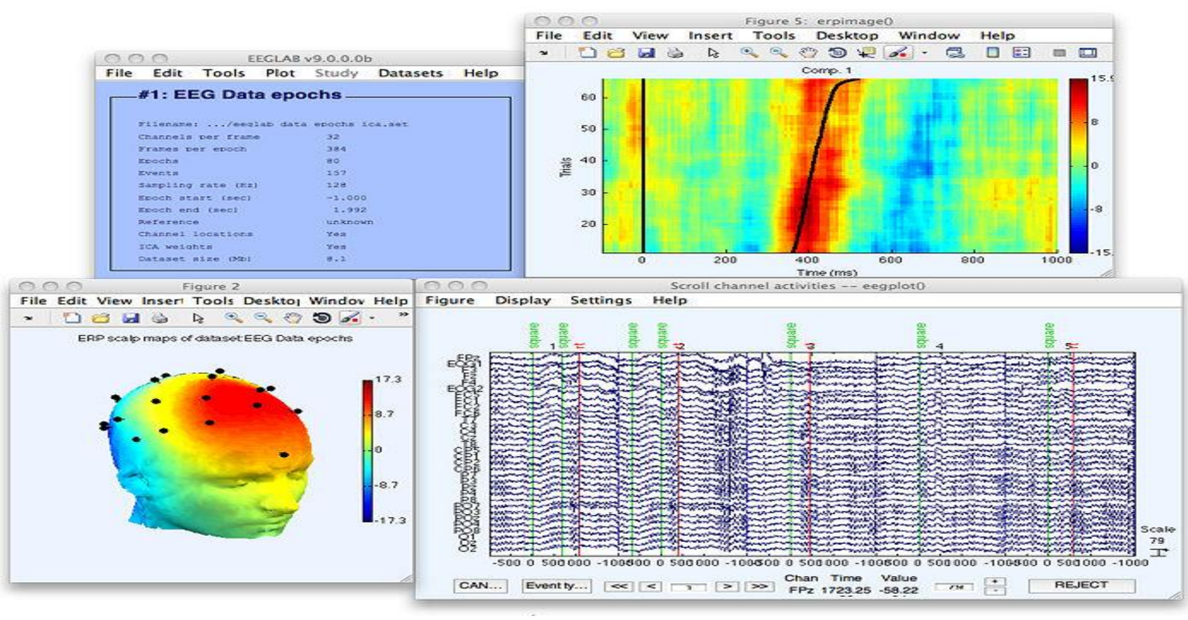


Figure 4.14: Screenshot of EEGLAB

EEGLAB has been widely used for analysis and visualization of EEG data in many research studies (Desjardins & Segalowitz, 2013; Viola, De Vos, Hine, Sandmann, Bleeck, Eyles, Debener, 2012; Zervakis, Michalopoulos, Iordanidou & Sakkalis, 2011). This indicates its wide acceptance as a good tool for EEG data analysis in the research community. Moreover, the fact that it is an open source tools makes it easily accessible since anybody can download it free of charge. This is why it was the preferred EEG data analysis tool for this dissertation as opposed to using commercial EEG data analysis tools like Bio-explorer and WinEEG that cost over $3000. Figure 4.14 below shows a screen capture of EEGLAB.

4.10.5. IBM SPSS

IBM SPSS is a statistical package developed by IBM Corporation and is used for statistical data analysis. IBM SPSS has a wide range of statistical commands that can be used for descriptive statistical analysis and inferential statistical analysis. Non-EEG data captured using the questionnaires in this dissertation were analysed using IBM SPSS Version 21. Figure 4.15 below depicts a screen capture of IBM SPSS.

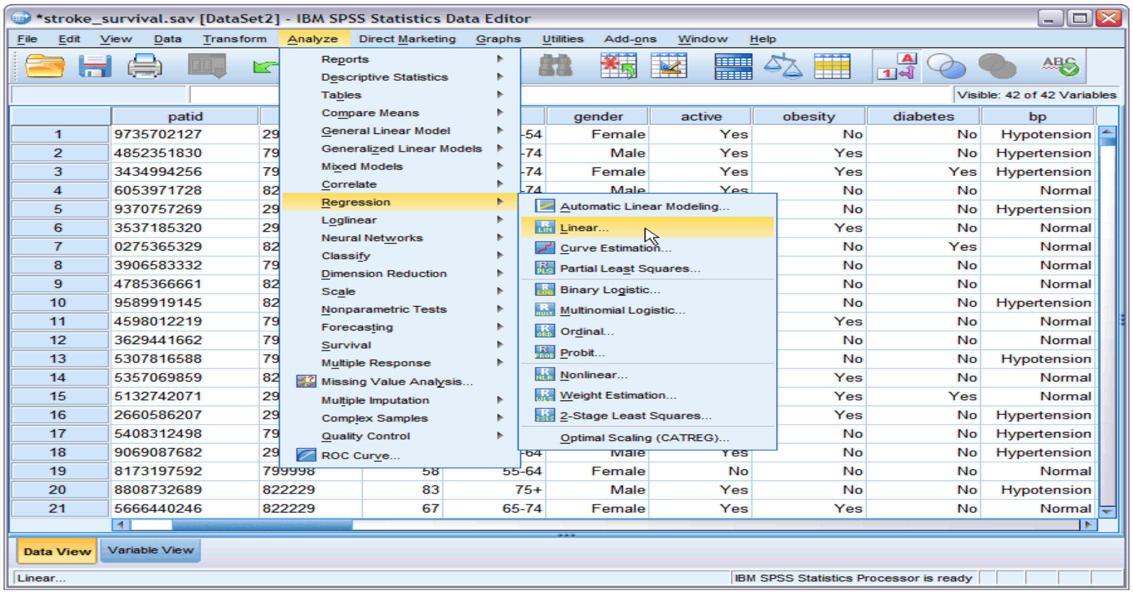


Figure 4.15: Screenshot of SPSS Version 21

4.10.6. EDF Browser Version 1.54

EDF Browser is open source software for processing EEG data developed by Van Beelen (n.d). EDF Browser was used in this study for processing EEG data and extracting information on the different brain activity. The version used in this study was version 1.54. A screen capture of EDF Browser is shown in Figure 4.16 below.

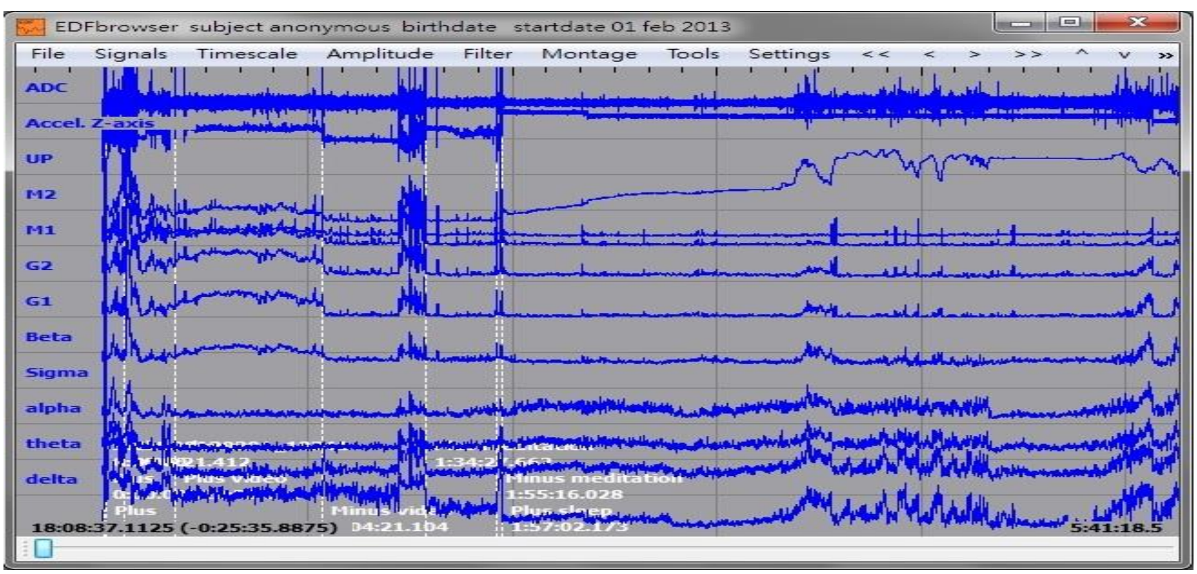


Figure 4.16: Screenshot of EDF Browser

4.11. Chapter Summary

This chapter presented a detailed description of the research process that was used in this dissertation. A review of existing research designs was presented and the most appropriate research design for this study (the longitudinal research design) was adopted and discussed in detail. Furthermore, the sampling process, data collection methods and measurements were discussed. Thereafter, the methodological steps of how the study was carried out are discussed. Lastly, the different types of analysis that were carried out with the collected data for the different measurements were discussed, as well as the research tools used in the study. The next chapter (chapter five) will present the data analysis and findings from the study.

CHAPTER FIVE

ANALYSIS AND DISCUSSION

5.1. Introduction

The previous chapter determined the research design and methodology adopted in this study, as well as the different measurements and tools used. In this chapter, the data analysis and findings will be presented. The main sections covered in the results and discussions are depicted in Figure 5.1 below.

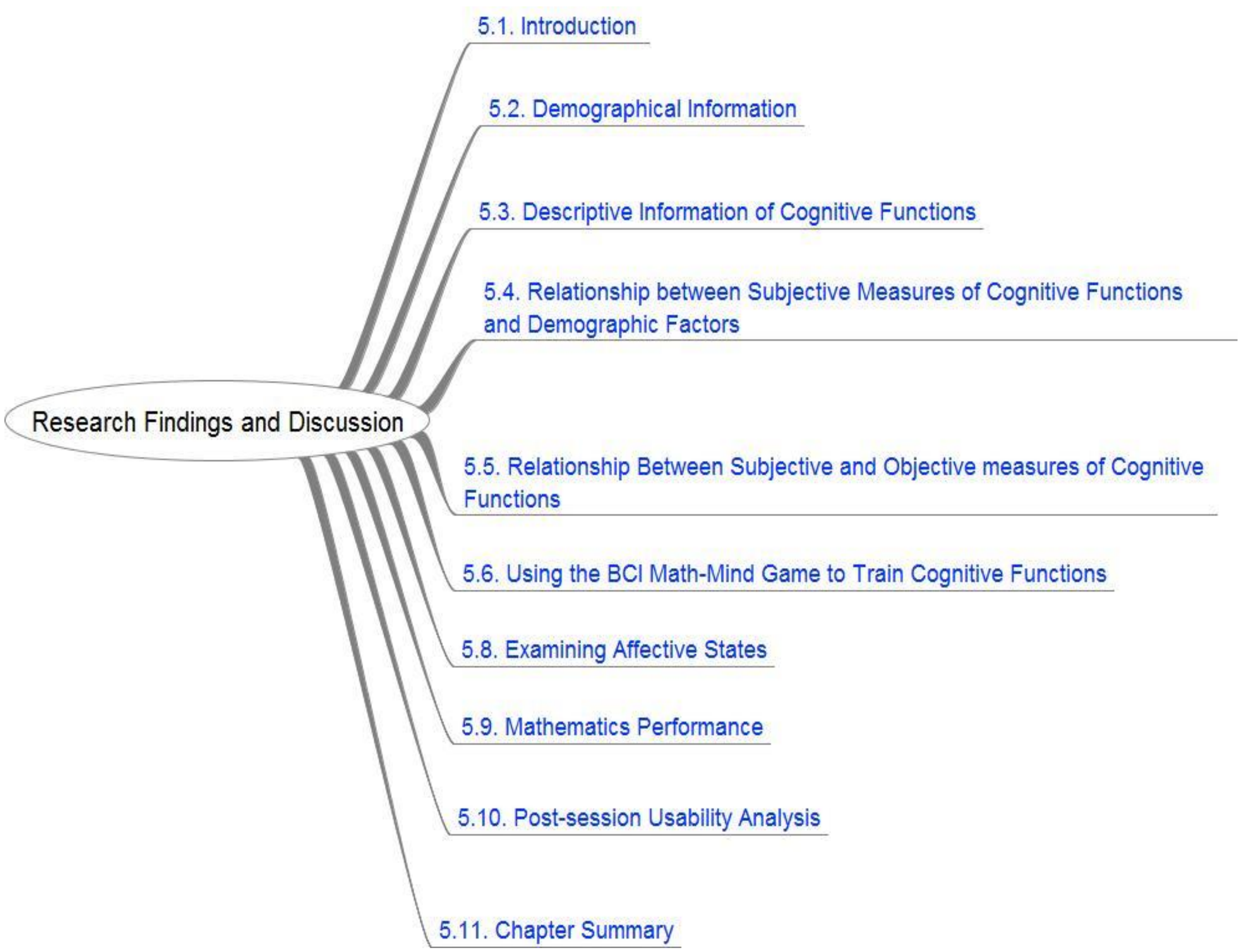


Figure 5.1: Mind-map of Chapter Five

5.2. Demographical Information

This section presents the general information of the participants that took part in the main study. A total of 36 participants took part. Of the 36 participants, 33 completed the two sessions and 3 completed only the first session.

5.2.1. Background of Participants

Of the 36 participants that took part in the study, 19 (52.8%) were females and 17 (47.2%) were males. It was vital to have a significant representative of both males and females as some cognitive functions (e.g. math anxiety) have been known to differ with gender. Most of the participants were Xhosa speaking. This was followed by Afrikaans speaking participants. Figure 5.2 and Figure 5.3 below present the graphical description of the gender and home language.

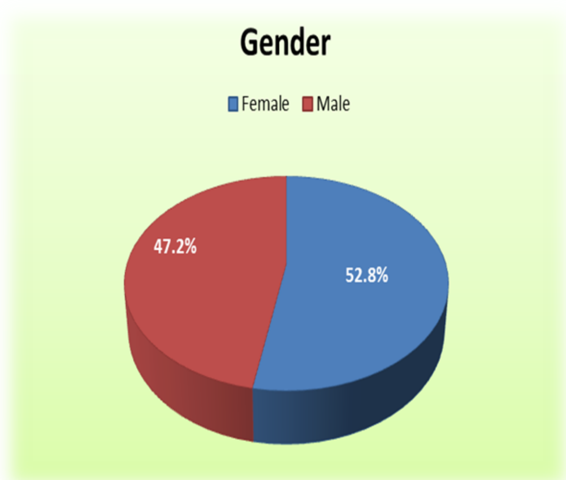


Figure 5.2: Gender

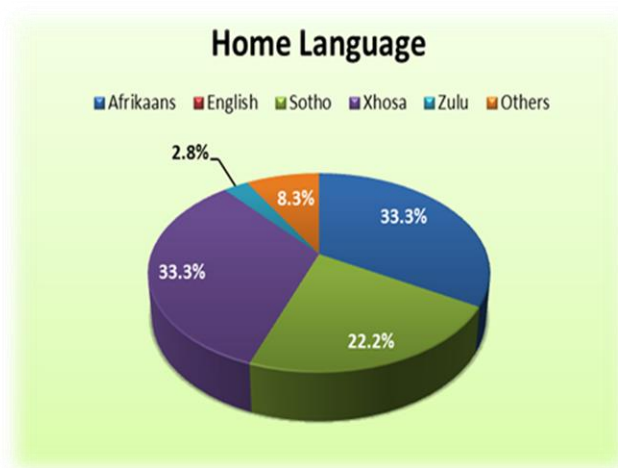


Figure 5.3: Home Language

All of the participants were students between grade five and grade eleven. The youngest participant was 10 years old and the eldest was 16 years. In order to provide a comprehensive description of the age and education level of the participants, the key descriptive statistics of these two variables are presented in Table 5.1 below.

Table 5.1: Descriptive Statistics of Participant Age and Education Level

Information	Age	Grade
Min	10	5
Max	16	11
Mean	14.12	8.44
Std. Dev	2.071	2.272
Skewness	-0.667	-0.256

The average age of the participants was 14.12 years. The standard deviation for age indicates that most of the participants were from the ages of 12 to 16. Additionally, the negative coefficient of skewness depicts that most of the participant's ages were to the right of the mean (greater than 14.12 years). With regards to education, the results depict that the least educated participant was in grade five and the most educated was in grade eleven, with a mean of 8.44. Also, it can be seen from the standard deviation that the participants were mostly between grade six and ten, with most of the participants higher than grade 8, as indicated by the negative coefficient of skewness. After examining the background characteristics of the participants, it is now important to examine their technology usage as the study is based on a technological intervention for mathematics education.

5.2.2. Participant's Technology Use

Two key technologies used in this study were a computer and a BCI. Participants were asked to indicate the technology they have used before, the frequency of use, and what it was used for. The findings for these two technologies are presented below.

5.2.2.1. Computer Usage

There was one participant (2.8%) who had never used a computer before. Most of the participants (38.7%) started using a computer about 6-12 months prior to this study. For the participants who have used a computer, most of them (42.9%) use a computer 1-2 times a week. Table 5.2 below presents detailed information of the computer usage of the participants.

Table 5.2: Participants' Computer Usage

	Total	Percentage
Computer Experience (Number of years of computer usage)		
None	1	2.8%
< 6 Months	2	5.6%
6 months – 1 year	14	38.9%
2 -3 years	4	11.1%
4-5 years	10	27.8%
> 6 years	5	13.9%
	36	**100**
****Frequency of Computer Usage***		
Daily	10	28.6%
More than twice a week	5	14.3%
1 -2 times a week	15	42.9%
Few times a month	1	2.9%
Few times a year	1	2.9%
Seldom	4	11.4%
	35	100%
****Computer Activities***		
Social Networking(e.g. Facebook, Twitter)	7	20%
Studying (e.g. researching school assignments)	27	77%
Surfing the Internet (e.g. Email)	7	20%
Playing games	15	42.8%
Shopping	0	0%
Other	0	0%

**Computer frequency and computer activities are based on the 35 participants who have used a computer before. The one participant without prior computer experience had to skip these questions.*

From Table 5.2 it is evident that most of the participants use a computer for studying and playing games, while none of the participants use a computer for shopping. This pattern is expected given the age group of the participants. The next technology usage examined was the BCI.

5.2.2.2. BCI Usage

Participants were asked to state whether they have used a BCI device before and if so, the purpose for which it was used. Out of all the 36 participants, none had used a BCI device before. As a result, all participants were treated as equals with regards to BCI experience. The relevance of this information for the preceding analysis was that there was no reason to control for the effect of prior BCI experience as all participants had the same experience level in this regards (i.e. zero).

5.2.3. Summary of Demographic Information

The demographic information provided an insight into the participants that took part in this study. The findings indicated an almost equal distribution of males and females in the study, which is important when making gender-related comparisons. Most of the participants had only started using a computer within six months prior to this study and none of them had used a BCI device before. This information is vital as it indicates whether it is necessary to control for the differences in technology competence when examining the cognitive functions. Most of the participants who had access to computers mostly used it for studying and playing games. This aligns with the view that children like playing computer games and supports the motivation for developing game-based educational interventions. The following section provides descriptive information on the cognitive functions measured with the use of the pre-test questionnaire.

5.3. Descriptive Information of Cognitive Functions

The pre-test questionnaire assessed the selected cognitive functions of the participants. Researchers in psychology, neuroscience, and mathematics education have developed a number of measurement scales for capturing cognitive functions. This study adopted some of these scales (see section 4.7 on measurements) to capture information on the cognitive functions (working memory, inhibitory control, number sense, and math anxiety) of the participants by means of the pre-test questionnaire. The results for each cognitive function are described below.

5.3.1. Working Memory

The working memory questionnaire (Appendix C) was used as the data capture tool for working memory and the results are presented in Table 5.3 below.

Working memory was classified into the three sub-categories (central executive, visuospatial working memory, and storage memory) that have been outlined in previous studies (Baddeley, 2003; Smedt *et al.*, 2009). From the results in Table 5.3, a smaller number depicts high working memory capacity, while a larger number depicts poor working memory capacity. Looking at the overall working memory components, it is seen that the participants had a higher visuospatial working memory (2.094), followed by the central executive working memory (2.14) and the storage working memory, which was the poorest (2.24). It was also observed that most of the participants found it difficult remembering what a person said when it was spoken fast. This explains why most participants had a low storage memory capacity and it has practical implications for teaching mathematics in schools - teachers need to avoid speaking fast so that students can remember. Most of the other questions had moderate to high ratings. The next cognitive function examined is the participant's level of inhibitory control.

Table 5.3: Working Memory Information

Statement	Mean	Std. Dev	Skewness
Central Executive			
Do you find it difficult to describe a step-by-step activity? For example, giving road directions.	1.85	1.132	1.638
When you are carrying out an activity, if you realise that you are making a mistake, do you find it difficult to change strategy?	2.18	1.585	0.953
Do you have difficulty in remembering what homework you have to do each day?	1.38	0.697	2.160
Do you find that you hesitate for a long time before choosing what you want in a shop?	2.79	1.343	-0.158
Overall Central Executive Score	**2.14**	**0.548**	**0.697**
Visuospatial Memory			
Do you need to make an effort to concentrate in order to follow a conversation in which you are participating with many other people?	1.38	0.551	1.075
When you are interrupted during an activity by a loud noise (door slam, car horn) do you have difficulty in getting back to the activity?	2.32	1.273	0.656
Do nearby conversations disturb you during a conversation with another person?	1.76	0.987	1.312
Do you find it difficult to carry out an activity in the presence of background noise (traffic, radio or television)?	2.88	1.387	0.078
Do you find that you get tired quickly during an activity which demands a lot of attention (for example, reading, or solving mathematics problems)?	2.12	1.250	0.953
Overall Visuospatial Memory Score	**2.094**	**0.562**	**0.155**
Storage Memory			
Do you have problems with remembering sequences of numbers, for example, when you have to note down a telephone number?	1.74	1.136	1.217
Do you find it difficult to remember the name of a person who has just been introduced to you?	1.56	1.160	2.078
Do you have difficulty remembering what you have read?	2.03	0.904	0.724
Do you need to re-read a sentence several times to understand what it says?	2.56	1.260	0.439
If somebody speaks quickly to you, do you find it difficult to remember what you were told or asked?	3.24	1.689	-0.113
Overall Storage Memory Score	**2.24**	**0.634**	**0.224**

5.3.2. Inhibitory Control

The subjective measures of inhibitory control were captured in the pre-test questionnaire using the EATQ scale (Appendix C). The obtained results are presented in Table 5.4 below.

Table 5.4: Participants' Level of Inhibitory Control

Statements on inhibitory control	Mean	Std. Dev	Skewness
It is hard for me not to open presents before I am supposed to.	2.97	1.696	0.088
When someone tells me to stop doing something, it is easy for me to stop	3.97	1.446	-1.288
The more I try to stop myself from doing something I should not do, the more likely I am to do it.	2.21	1.250	0.871
It is easy for me to keep a secret.	4.00	1.437	-1.253
I can stick with my plans and goals.	3.97	1.062	-0.624
***Overall Score**	**3.735**	**0.634**	**-0.455**

**Overall score is obtained by rotating the first and the third statements so that a high score reflects a level of high inhibitory control*

The statements for computing inhibitory control were both positively and negatively worded. To compute the overall inhibitory control score, the two negatively worded statements were rotated so that a higher score indicated a high level of inhibitory control. The results showed that most of the participants had a high level of inhibitory control (3.735). Specifically, most of the participants specified that they could easily keep a secret, stop doing something when required, and stick to pre-planned objectives. The next cognitive function examined was math anxiety.

5.3.3. Math Anxiety

Math anxiety was determined using the FSMAS questionnaire (Appendix C). Similar to the inhibitory control scale, the FSMAS is both positively and negatively worded. The negatively worded states were rotated in computing the overall math anxiety score so that a higher score indicated a high level of math anxiety. The obtained results are presented in Table 5.5 below.

Table 5.5: FSMAS Measures of Math Anxiety

Statements	Mean	Std. Dev	Skewness
Mathematics does not scare me at all.	1.62	0.922	1.13
It would not bother me at all to take more mathematics courses.	2.74	1.62	0.14
I usually do not worry about my ability to solve mathematics problems.	2.24	1.44	0.86
I have always been at ease during mathematics tests.	2.41	1.28	0.35
Mathematics makes me feel uncomfortable and nervous.	3.91	1.29	-0.82
I always feel tense when I think of trying hard mathematics problems.	3.74	1.26	-0.52
My mind goes blank and I am unable to think clearly when working mathematics.	3.85	1.44	-1.09
Mathematics makes me feel uneasy and confused.	3.41	1.37	-0.29
Overall Math Anxiety Score	**2.26**	**0.93**	**0.504**

The average overall math anxiety score was 2.26 with a positive coefficient of skewness indicating that most participants had medium to low levels of math anxiety. This score is slightly lower than that of previous studies in South Africa (Mutodi & Ngirande, 2014; Hlalele, 2012). However, these studies used a larger sample with most of their participants above 16 years. It is imperative to acknowledge this difference in age groups as prior studies (Woodard, 2004; Balogˇlu & Koçak, 2006; Mutodi & Ngirande, 2014; Verkijika & De Wet, 2015) have indicated a significant relationship between math anxiety and age. This relationship is examined in section 5.4.2 below. The next cognitive function examined was number sense.

5.3.4. Number Sense

Based on questions from the NST (Appendix C), number sense was captured and the findings expressed on a level of one to five, with one being a low level of number sense and five being high. The findings are presented in Figure 5.4 below.

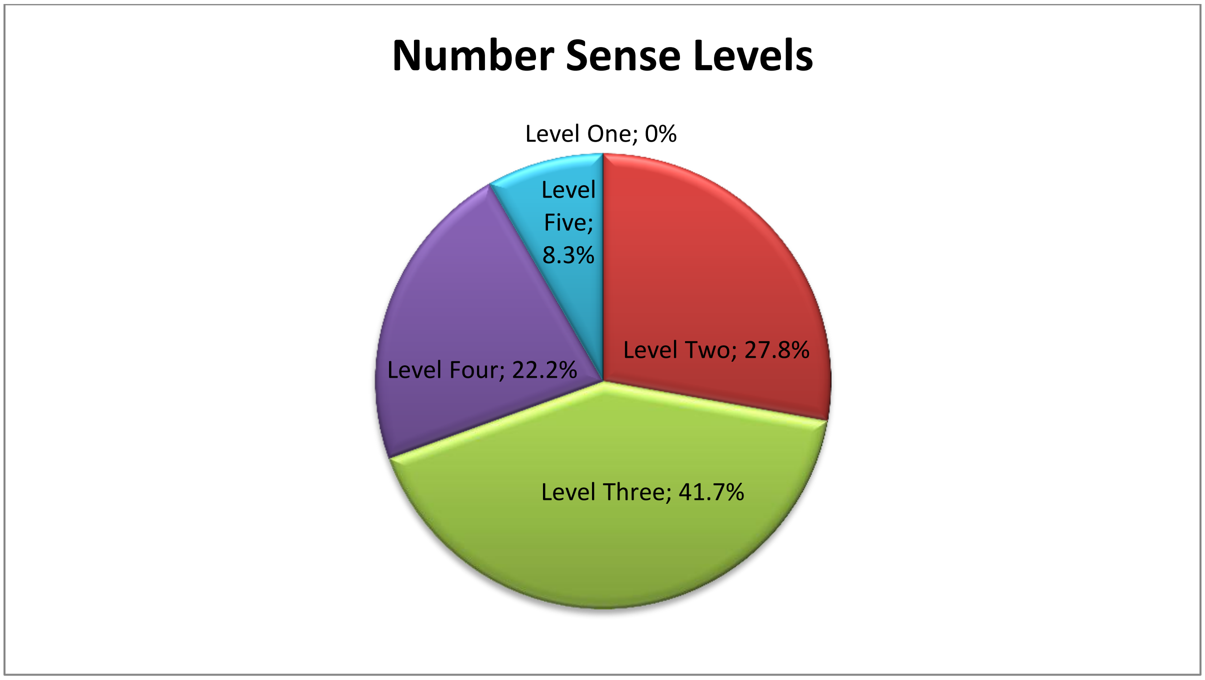


Figure 5.4: Levels of Number Sense based on the NST

The results showed that most of the participants were in level three range of the number sense, indicating a moderate level of number sense among most participants. About 30.5% of the participants had a high level of number sense (level four and five), while 27.8% had a low level (level one and two). The next subsection provides the summary of the cognitive functions.

5.3.5. Summary of Cognitive Functions

After examining the level of the four cognitive functions (working memory, inhibitory control, math anxiety, and number sense) among the participants in this study, a couple of findings were revealed. Firstly, it was seen that the highest component of working memory among the participants was the visuospatial working memory, followed by the central executive and then the storage working memory. Secondly, the level of inhibitory control was high among the participants. Thirdly, the level of math anxiety among the participants was medium to low. Lastly, it was seen that the level of number sense was moderate among most of the participants. These findings provided the basis for understanding the level of cognitive functions among the participants based on existing subjective scales. Before using the findings from these scales in cross-sectional analysis, it is imperative to examine the validity and reliability of the subjective scales for cognitive functions, which is examined in the next section.

5.4. Relationship between Subjective Measures of Cognitive Functions and Demographic Factors

Cognitive functions have been known to vary across different demographic groups (e.g. age, gender, and education). However, there have been contradictory findings (Birgin, Baloğlu, Çatlıoğlu & Gürbüz, 2010; Dede, 2008; Devine, Fawcett, Szucs & Dowker, 2012; Ho *et al.*, 2010; Jain, 2009; Mutodi & Ngirande, 2014; Tapia, 2004; Yüksel-Şahin, 2008), especially with regards to gender. This study examined these relationships in this section as a means of contributing to the ongoing bulk of knowledge.

5.4.1. Gender and Cognitive Functions

Figure 5.5 below presents the mean for the cognitive functions for males and females, while the ANOVA results in Table 5.6 depicts the statistical differences in gender across the different cognitive functions. The findings in Figure 5.5 indicate that females have a higher central executive working memory, storage memory, inhibitory control, number sense, and math anxiety than males. A higher value is, however, not good with respect to math anxiety, as a lower math anxiety is more desirable.

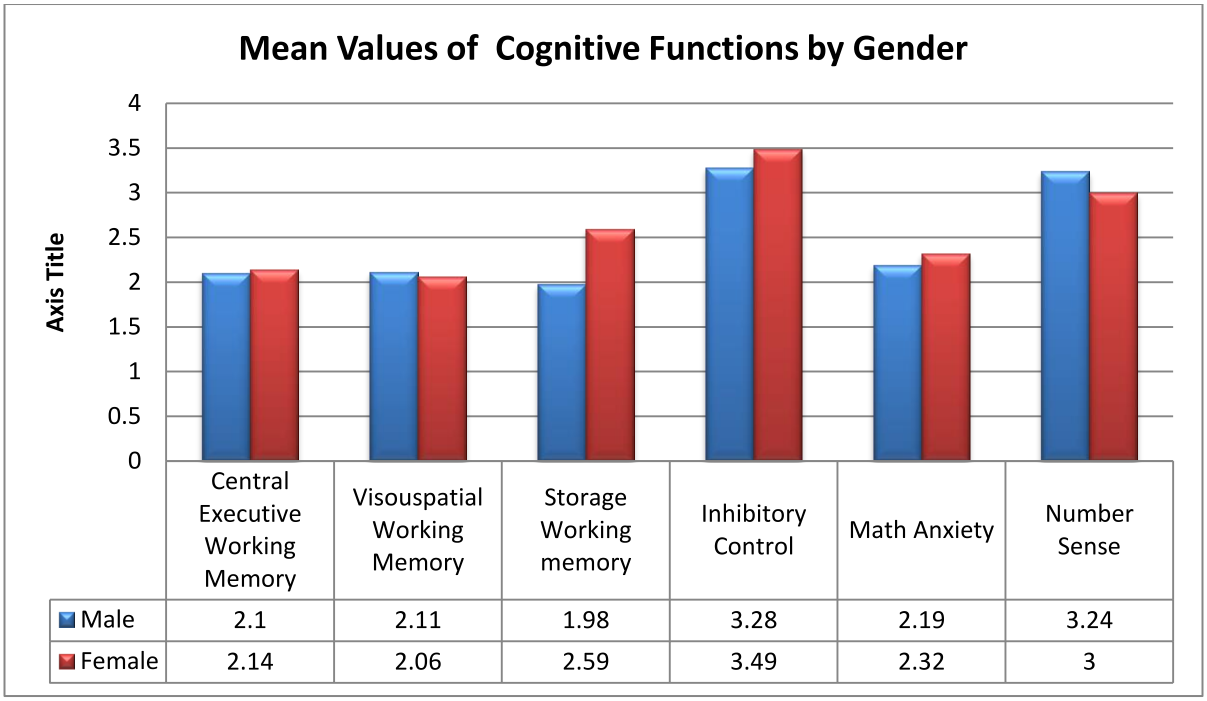


Figure 5.5: Gender Differences in Cognitive Functions

Males only have a higher visuospatial working memory than females. This finding is consistent with prior studies (De Frias, Nilsson & Herlitz, 2006; Geiser, Lehmann, Corth & Eid, 2008; Millet, Raoux, Le Carret, Bouisson, Dartigues & Amieva, 2009) that have also shown that males tend to have a higher visuospatial memory than females. It is also seen that the mean values, especially for central executive working memory and visuospatial working memory, are almost the same, showing that the differences might not be too vast. To determine if the differences are significant, an ANOVA analysis (Table 5.6) was computed.

The results in Table 5.6 indicated that only the storage memory had a significant difference based on gender. It can thus be concluded that females have a higher storage memory than males.

The finding is congruent with a study by Lewin, Wolgers and Herlitz (2001) who also indicated this result.

Table 5.6: ANOVA Analysis for Cognitive Functions based on Gender

Cognitive Functions	ANOVA Test	
	F-Value	**P-Value**
Central Executive Working Memory	0.061	0.806
Visuospatial working memory	0.050	0.824
Storage Working Memory	10.562	0.003***
Inhibitory Control	0.750	0.393
Math Anxiety	0.198	0.659
Number Sense	0.581	0.451

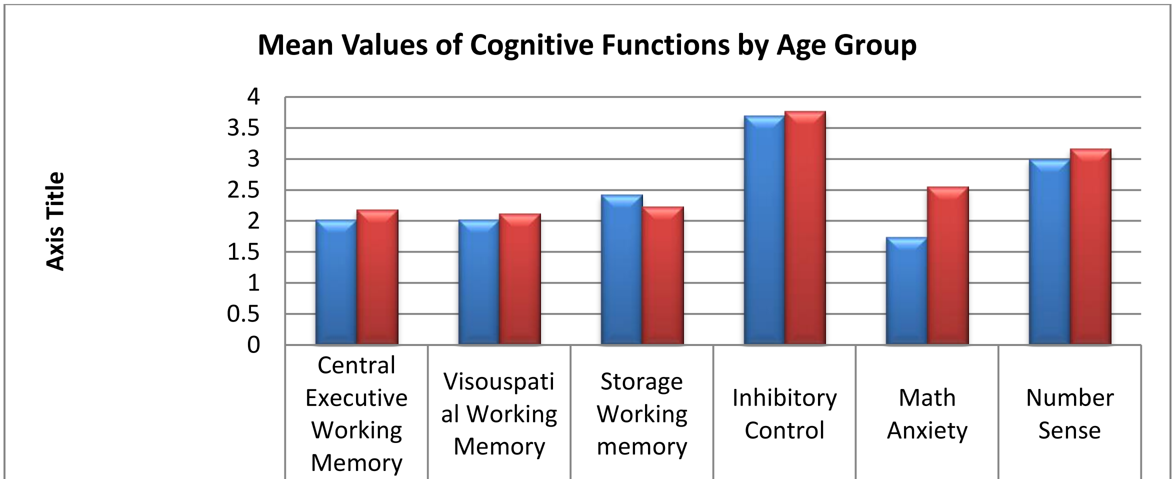
*** P<0.01

With regards to gender differences in math anxiety, there have been significant debates over the years. Although the descriptive data in Figure 5.5 indicated that females had a higher math anxiety than males, as also alluded by several studies (Devine *et al.*, 2013; Ho *et al.*, 2010; Jain, 2009; Mutodi & Ngirande, 2014), the ANOVA analysis showed that the differences were not significant. As such, the findings here support the school of thought that there are no gender differences in math anxiety (Birgin *et al.*, 2010; Dede, 2008; Tapia, 2004), while at the same time opposing the view that females tend to have higher math anxiety than males. Also, females have been known to have a higher level of inhibitory control than males (Yuan, He, Qinglin, Chen & Li, 2008). Even though this pattern was seen in this study (Figure 5.5) the findings were not statistically significant (Table 5.6). Nonetheless, it is imperative to acknowledge that Yuan *et al.* (2008) used older participants compared to those in this study. Such differences could be moderated by age differences. Lastly, there was no significant difference in the level of number sense based on gender and this finding is consistent with existing evidence (Libertus, Feigenson

& Halberda, 2011; Tosto *et al.*, 2014). The next section examines how cognitive functions differed by age group.

5.4.2. Age and Cognitive Functions

Figure 5.6 below presents the mean for the cognitive functions for males and females, while the ANOVA results in Table 5.7 depict the statistical differences in gender across the different cognitive functions.



	Central Executive Working Memory	Visouspatial Working Memory	Storage Working memory	Inhibitory Control	Math Anxiety	Number Sense
Less than 14 years	2.02	2.02	2.42	3.7	1.74	3
14 years or more	2.18	2.12	2.23	3.77	2.55	3.17

Figure 5.6: Differences in Cognitive Functions by Age

The results in Figure 5.6 depicted that older participants have a higher central executive working memory, visuospatial working memory, inhibitory control, and math anxiety than younger participants. Graphical observation of Figure 5.6 indicates that the biggest difference based on age group is found for math anxiety. It has been widely suggested that math anxiety increases with age (Balogˇlu & Koçak, 2006; Mutodi & Ngirande, 2014; Woodard, 2004; Verkijika & De Wet, 2015). In order to examine if these differences in cognitive functions across age groups were significant, an ANOVA analysis was performed (Table 5.7).

Table 5.7: ANOVA for Cognitive Functions based on Age Group

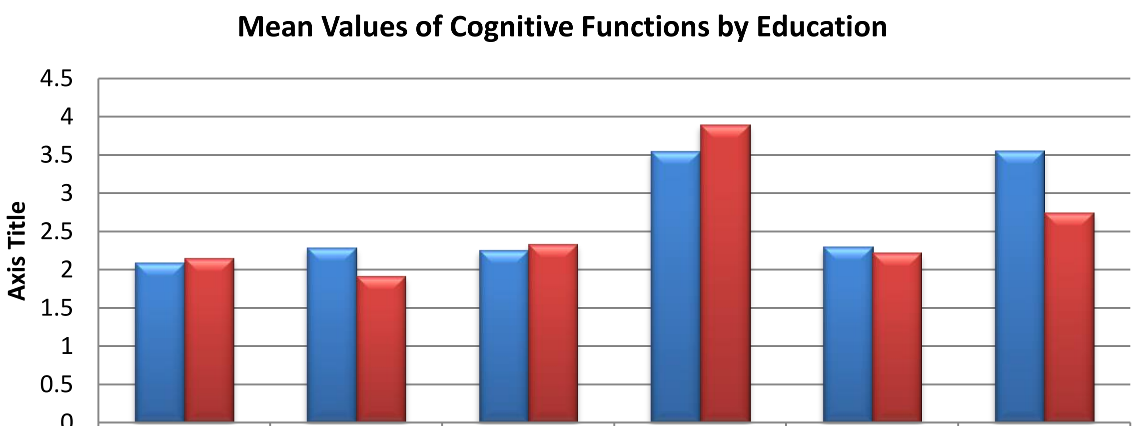
Cognitive Functions	ANOVA Test	
	F -Value	**P-Value**
Central Executive Working Memory	0.889	0.353
Visuospatial working memory	0.289	0.594
Storage Working Memory	0.706	0.407
Inhibitory Control	0.070	0.793
Math Anxiety	8.342	0.007***
Number Sense	0.291	0.593

*** p<0.01

The findings showed that only math anxiety differed significantly by age group. This supports the views of prior researchers (Balogˇlu & Koçak, 2006; Mutodi & Ngirande, 2014; Woodard, 2004) that math anxiety increased with age. None of the working memory components showed a significant difference. This could be attributed to the small interval of the age group (9-16 years), as prior studies have mostly compared teenagers to children and older adults. Generally, working memory increases with age to a peak value and starts decreasing with ageing (Daisuke, Mariko, Naoyuki, Visser, & Jun, 2014; Fandakova, Sander, Werkle-Bergner & Shing, 2014). In comparison with Daisuke *et al.* (2014) and Fandakova *et al.* (2014), the age group range in this dissertation was too small to decipher such patterns in working memory. With regards to inhibitory control, although older participants showed a slightly higher level of inhibitory control (Figure 5.6), the findings were not significant. As such, this study failed to support the recent empirical evidence (Macdonald, Beauchamp, Crigan, & Anderson, 2014) that inhibitory control increases with age. Similarly, there was no significant difference in the level of number sense across the different age groups. Children of the same age group (even as young as few months old babies) already show differences in their level of number sense, suggesting that number sense could be influenced by some genetic factors (Libertus & Brannon, 2009; Totso *el al.*, 2014). While some cognitive functions vary with age, it is also possible that other cognitive functions could be more affected by education, as learning is one way of developing cognitive functions. The next section examined the differences in cognitive functions by educational attainment.

5.4.3. Education and Executive Functions

The results for differences in cognitive functions based on educational background are presented in Figure 5.7 and Table 5.8 below.



	Central Executive Working Memory	Visuospatial Working Memory	Storage Working Memory	Inhiitory Control	Math Anxiety	Number Sense
FET	2.09	2.29	2.26	3.55	2.3	3.56
GET	2.15	1.92	2.34	3.9	2.22	2.75

Figure 5.7: Educational differences in Cognitive functions

In line with the classification of schooling in South Africa by the South African Department of Basic Education (DBE, 2011), this dissertation grouped the participants into two groups namely: General Education and Training (GET) and Further Education and Training (FET). GET is made up of learners from grade 0 to grade 9, while FET comprises of learners from grade 10 to grade 12, plus higher education vocational training facilities. The results showed that GET students had a higher central executive working memory, storage working memory, and inhibitory control than FET students. In order to examine the significance of these findings, an ANOVA analysis (Table 5.8) was performed.

Table 5.8: ANOVA analysis for Cognitive functions based on Education group

Cognitive Functions	ANOVA Test	
	F-Value	**P-Value**
Central Executive Working Memory	0.107	0.745
Visuospatial working memory	4.102	0.045**
Storage Working Memory	0.110	0.742
Inhibitory Control	3.025	0.091
Math Anxiety	0.068	0.795
Number Sense	8.423	0.006***

***p< 0.01; ** P<0.05

From Table 5.8, it is evident that only the visuospatial working memory and number sense had a significant difference across the different educational groups. Visuospatial working memory has been shown to mature around the age of 12 years (Mürner-Lavanchya *et al.*, 2014; Spencer-Smith, Ritter, Mürner-Lavanchy, El-Koussy, Steinlin & Everts, 2013). While prior studies (Mürner-Lavanchya *et al.*, 2014; Spencer-Smith *et al.*, 2013) have established age differences in visuospatial working memory, the findings in this study suggest that such differences could be accounted for or mediated by the level of education. The significant difference for number sense indicates that children with a higher level of education are more likely to have a higher level of number sense than those below them in academic terms. This finding is congruent with the allusion by Ashcraft and Moore (2012) that education and the continuous acquisition of knowledge were vital in the development of number sense.

5.4.4. Summary of Cognitive Function across Demographic Factors

Determining whether or not cognitive functions vary based on demographic factors has been a keen interest for many researchers. Three demographic factors (gender, age, and education) were used in this study. The findings showed significant gender differences in storage memory, with females having more storage memory. Similarly, there were significant age differences in the levels of math anxiety with older participants having a higher level of math anxiety. With regards to education, there were significant differences in terms of visuospatial working memory and number sense with both cognitive functions increasing with educational level.

After examining these relationships, the next step was to examine if the subjective measures of cognitive functions captured with widely used and approved scales were similar to the measures captured with the BCI device.

5.5. Relationship between Subjective and Objective Measures of Cognitive Functions

Similar to prior studies (Alloway, 2007a; Cates & Rhymer, 2003; Houben, 2011; Wang & Shah, 2014), the participants were classified into two groups (high and low group for each cognitive function) based on their overall cognitive function scores (Section 5.3). The median overall cognitive function score for all participants in the study was used as the separation point, with participants being classified as having a low cognitive function if they scored at or below the median, and a high cognitive function if the scored above the median. Cates and Rhymer (2003) elucidate that this approach of using the median is superior to other approaches because it controls for any artificially inflated differences between groups often observed in methods that classify the groups based on the upper and lower quartile scores. After classifying the participants into high and low cognitive function groups, an independent sample t-test was used to compare the differences in the BCI measured cognitive functions for the first attempt that the participants played each of the two game levels. Only the first attempt on each game level (task 1 and task 2) was used, because it was expected that by the second attempt at playing the same level, he/she had already received feedback on cognitive functions (from the first attempt), with guidance included on how to train the cognitive function. As such, the cognitive function during the second gameplay will already be influenced by prior bio-feedback and training using the BCI. The results of the independent sample t-test for each of the cognitive functions are presented in the subsections below.

5.5.1. Working Memory

Working memory was classified based on the three components (central executive, visuospatial, and storage working memory). For each of the components, the median values were used to classify participants into the high and low working memory component groups. The results for each of these components are discussed below.

5.5.1.1. Central Executive Working Memory

Participants were classified into low and high central executive working memory groups and the two groups were compared using the objective measure of working memory with the BCI application. The results are shown in Table 5.9 below. The results showed that the high central executive working group had a significantly higher BCI measured working memory than the low central executive group.

The differences in the BCI measured working memory were significant for all three cases compared (level one task, level five tasks, and the average for the two tasks). This provided significant evidence that a participant's central executive memory captured with the working memory questionnaire was similar to the level of working memory captured with the BCI.

Table 5.9: Comparing WMQ – CE scores to WM scores of the BCI-based System

	Mean Working Memory Values		T-test for equality of means			95% Confidence Interval of the Mean Difference	
	Low CE Group	High CE Group	Mean Difference	T-Value	P-Value	Lower	Upper
Level One WM	71.63	79.33	-7.70	-3.145	0.004***	-12.69	-2.71
Level Five WM	61.15	73.52	-12.37	-2.479	0.019**	-22.53	-2.20
Average WM	66.39	76.42	-10.03	-3.063	0.004***	-16.71	-3.36

***$P < 0.01$; ** $P < 0.05$; CE = Central executive; WM = Working memory

These findings support existing views that working memory has a close relationship to attention (Baddeley, 2003; Berman & Moore, 2008; Bleckley *et al.*, 2003; Conway *et al.*, 2001; Jonides *et al.*, 2008; McElree, 2006). As such it is plausible to use the affective measure of attention from the BCI device as a key component of objectively measuring working memory, as it yields similar results as proven subjective measures of central executive working memory. The next component of working memory examined was the visuospatial working memory.

5.5.1.2. Visuospatial Working Memory

Participants were classified into low and high visuospatial working memory groups and the two groups were compared using the objective measure of working memory with the BCI application. The results are shown in Table 5.10 below.

Table 5.10: Comparing WMQ – VSM scores to WM scores of the BCI-based System

	Mean Working Memory Values		T-test for equality of means			95% Confidence Interval of the Mean Difference	
	Low VSM Group	High VSM Group	Mean Difference	T-Value	P-Value	Lower	Upper
Level One WM	78.04	76.62	1.42	0.578	0.567	-3.59	6.44
Level Five WM	70.89	69.67	1.22	0.253	0.802	-8.58	11.01
Average WM	74.47	73.14	1.32	0.402	0.690	-5.37	8.01

VSM- visuospatial working memory

The results indicated that there was no significant difference in the BCI measured working memory between the low and high visuospatial working memory groups. This suggests that the BCI measured working memory cannot be used as a measure of visuospatial working memory. Nonetheless, the results seem plausible as visuospatial working memory focuses mostly on identifying and storing things like shapes, colours, and objects, as opposed to the mathematical equations in the BCI Math-Mind game in this study. As such, studies wishing to adopt BCI paradigms for examining visuospatial working memory should develop BCI applications similar to the Cambridge Neuropsychological Test Automated Battery (CNTAB)[6] section for measuring visuospatial working memory. The next component of working memory examined was the storage working memory.

5.5.1.3. Storage Working Memory

Participants were classified into low and high storage working memory groups and the two groups were compared using the objective measure of working memory with the BCI application. The results are shown in Table 5.11 below.

[6] For more information on the CNTAB see Falconer et al. (2010) and Syväoja et al. (2014)

Table 5.11: Comparing WMQ – Storage WM scores to WM scores of the BCI-based System

	Mean Working Memory Values		T-test for equality of means			95% Confidence Interval of the Mean Difference	
	Low VSM Group	High VSM Group	Mean Diff.	T-Value	P-Value	Lower	Upper
Level One WM	74.93	81.63	-6.70	-3.577	0.001***	-10.52	-2.88
Level Five WM	66.76	76.63	-9.86	-2.091	0.045**	-19.47	-0.26
Average WM	70.84	79.13	-8.28	-3.084	0.004***	-13.75	-2.81

****P<0.01; ** P < 0.05*

The results showed that the high storage working group had a significantly higher BCI measured working memory than the low storage group. This shows that storage memory could be objectively measured with the BCI math-mind game. These findings seem plausible as the second component of the BCI measured working memory included accurately remembering standard multiplication tables with maintaining a predetermined minimum attention level. This is in line with prior findings (Grube & Barth, 2004; Holmes & Adams, 2006) that storage memory (phonological loop) is concerned with the retrieval of basic mathematical facts. After examining this last component of working memory, the next cognitive function (inhibitory control) was analysed.

5.5.2. Inhibitory Control

Participants were classified into low and high inhibitory control groups and the two groups were compared using the objective measure of inhibitory control in the BCI based stop-signal task. The results are shown in Table 5.12 below.

Table 5.12: Comparing Subjective Inhibitory Control scores to Inhibitory Control scores of the BCI System

	Mean Inhibitory Control Values		T-test for equality of means			95% Confidence Interval of the Mean Difference	
	High IC Group	Low IC Group	Mean Diff.	T-Value	P-Value	Lower	Upper
Level One IC	37.00	21.92	15.08	2.864	0.007***	4.36	25.80
Level Five IC	34.57	19.85	14.73	3.672	0.001***	6.56	22.90
Average IC	35.79	20.88	14.90	4.411	0.000***	8.02	21.78

****$P < 0.05$;* IC = inhibitory Control

The results showed that the high inhibitory control group had a significantly higher BCI measured inhibitory control than the low storage group. This confirms the fact that, as previously established, the stop signal task is a good measure of inhibitory control (Carter *et al.*, 2003; Ray *et al.*, 2006; Sakajiri & Maekawa, 2007; Sylwan, 2004; Verbruggen & Logan, 2008). Moreover, it adds to existing knowledge as the BCI-based stop signal task uses brain cognitive commands as opposed to keyboard commands used in previous stop signal tasks. The practical implication of this is that people with disabilities can now use the BCI-based stop signal task to train their inhibitory control. The next cognitive function examined was math anxiety.

5.5.3. Math Anxiety

Participants were classified into low and high math anxiety groups and the two groups were compared using the objective measure of math anxiety using the BCI-based physiological arousal. The results are shown in Table 5.13 below.

Table 5.13: Comparing FSMAS scores to Math Anxiety scores of the BCI-based System

	Mean Anxiety Values		T-test for equality of means	
	High Math Anxiety Group	Low Math Anxiety Group	T-Value	P-Value
Level One Math Anxiety	58.360	46.706	1.430	0.163
Level Five Math Anxiety	59.193	36.658	2.376	0.024**
Average Math Anxiety	58.777	43.182	2.174	0.037**

** $p < 0.05$

The results in Table 5.13 indicated that the high math anxiety group from the FSMAS had a higher mean BCI-measured math anxiety compared to the low math anxiety group. The results are, however, not significant for level one of the Math-Mind game. This could possibly result from the fact that level one math exercises were very easy and, therefore, exerted a limited amount of math anxiety from most of the participants. Nonetheless, the results for level five of the Math-Mind game and the average for both levels are significant at the 5% level. This clearly depicts that the level of math anxiety measured with the FSMAS is significantly related to that measured with the BCI. This finding supports the view of prior studies (Medeiros and Leclercq, 2007; Mattarella-Micke *et al.*, 2011) that math anxiety can be measured in terms of physiological arousal. The next cognitive function examined was number sense.

5.5.4. Number Sense

Following the classification of number sense in section 5.3.4, an ANOVA analysis was used to determine if the subjective measure of number sense was related to the number sense measured with the number sense measurement during the first session. The ANOVA analysis showed significant differences ($F = 94.295$ and $p < 0.01$) between the three groups (low, medium, and high number sense groups). Post hoc analysis of the ANOVA results using the Scheffe test was performed and the findings are presented in Table 5.14 below.

Table 5.14: Post Hoc Multiple Comparisons for Number Sense

	Low	Moderate
Moderate	17.56***	
High	39.12***	21.56***

*** $p < 0.01$

The findings showed significant differences in number sense across the three groups. The mean difference between the low and medium number sense groups is 17.56, while that between the low and high group is 39.12. Similarly the mean difference between the high and moderate number sense group is 21.56. All mean differences are statistically significant, showing that the high number sense group recorded a higher level of number sense during the session compared to the moderate and low groups. Also, the moderate group recorded a statistically significant higher level of number sense during the session compared to the low number sense group. This indicates consistency between the subjective and objective measures of number sense used in this study.

5.5.5. Summary of Relationship between Subjective and Objective Measures of Cognitive Functions

Examining the relationship between the subjective and objective measures of cognitive functions was important in determining the consistency of measures adopted in the study. The findings indicated that BCI-based measure of working memory was related to the subjective measure of central executive working memory and storage working memory, but not the visuospatial working memory. The results also showed a statistically significant association between the subjective and objective measures for inhibitory control, math anxiety, and number sense. After establishing these associations, the next section focuses on the ability of using the Math-Mind BCI-based system to enhance cognitive functions.

5.6. Using the BCI Math-Mind Game to Train Cognitive Functions

After the analysis of section 5.5, it was seen that the cognitive functions measured with the BCI and Math-Mind game were a reflection of the subjectively measured cognitive functions from established scales. This validated the BCI captured cognitive functions and the next step was to evaluate if the participants used the neuro-feedback from the BCI to control and enhance their cognitive functions. In order to achieve this, a paired sample t-test was used for each cognitive function. In total, there were eight tasks across two sessions, with four tasks per session. The eight tasks were subdivided into two groups of four tasks each. Each of these groups represented the number of times a specific game level was played. Henceforth the first group is referred to as the easy mathematics group (EM) which represents the attempts where level one of the Math-Mind game was played. The second group will be referred to as the difficult mathematics group (DM) which represents the attempts that level five of the Math-Mind game was played. The analysis for each of the cognitive functions is presented in the subsections below. Task one and task two represent the first session, while tasks three and four represent the second session. Just to reiterate, it should be noted that the second sessions occurred on a different day from the first session.

5.6.1. Enhancing Working Memory

Working memory was recorded for each of the four tasks for each group. The findings are presented in Table 5.15 below.

Table 5.15: Paired sample T-test for Working Memory

Pairs (P)	N	Mean Working Memory Values				T-test for equality of means			95% Confidence Interval of the Mean Difference	
		1st Task	***2nd Task***	***3rd Task***	***4th Task***	***Mean Diff.***	***T-Value***	***P-Value***	***Lower***	***Upper***
Panel A: Level One Game Play Across the Two Sessions										
EM One	36	77.47	80.72	-	-	-3.31	-3.159	0.003**	-5.43	-1.18
EM Two	33	76.95	-	79.74	-	-2.79	-3.563	0.001**	-4.38	-1.19
EM Three	33	75.27	-	-	80.62	-5.36	-2.456	0.022*	-9.89	-0.84
EM Four	33	-	80.21	78.85		1.36	1.197	0.244	-0.99	3.72
EM Five	33	-	80.21	-	80.62	-0.41	-0.316	0.755	-3.12	2.30
EM Six	33	-	-	78.85	80.62	-1.77	-0.969	0.343	-5.57	2.02
Panel B: Level Five Game Play Across the Two Sessions										
DM One	36	70.92	77.27	-	-	-6.35	-4.786	0.000**	-9.04	-3.66
DM Two	33	69.86	-	77.54	-	-7.69	-3.472	0.002**	-12.20	-3.18
DM Three	33	69.86	-	-	80.99	-11.13	-5.023	0.000**	-15.64	-6.62
DM Four	33	-	76.76	77.54	-	-0.79	-0.505	0.617	-3.98	2.40
DM Five	33	-	76.76	-	80.99	-4.23	-2.663	0.012*	-7.47	-0.99
DM Six	33	-	-	77.54	80.99	-3.44	-2.845	0.008*	-5.91	-0.98

$**p < 0.01$; $* p < 0.05$

Pair EM one showed a significant difference in working memory for the first two attempts of the EM task during the first session. The mean working memory value for the second attempt is significantly higher than the first attempt, indicating that enhancement of working memory occurred during the first session. Pair EM two compared the first attempt in the first session to the first attempt in the second session for the EM task. This pair also showed a significantly higher working memory for the second session, indicating that the working memory can be trained and maintained over days. Pair EM three indicated the comparison between the first attempt (session one) and the last attempt (session two) of the EM task. The last attempt was significantly higher than the first attempt, indicating that working memory was significantly enhanced for the duration of the study (i.e. across two sessions).

Pairs EM four, EM five and EM six showed no significant differences in the attempts. These pairs compared the second attempt for the EM task in the first session to the first (EM four) and second (EM five) attempts in the second session. EM six focused on the two attempts during the second session. Although there was a small increase during the second session, it was not statistically significant, showing that as the working memory training continuous, it becomes difficult to see significantly huge changes. However, when you compare from where the participant started to the end of the session, the difference is quite significant, showing that training of working memory increases and reaches a point where it starts to increase in much smaller quantities.

For the DM task, the only pair that did not show a statistically significant difference in working memory was pair DM four. This pair compared the second DM task for the first session with the first DM task in the second session. Although the DM task in the second session was slightly higher, the difference is insignificant. This could possibly be attributed to the time gap between the first and the second session, suggesting that continuous play enhances the working memory. The significant findings from all the other pairs indicated that working memory can actually be enhanced with the BCI Math-Mind application. These results are congruent with those of Lee *et al.* (2013) which showed that a BCI device could be used to significantly enhance working memory. The difference between the first and the last task is the best indication of a huge increase in working memory from the first task in session one to the last task in session two. Next inhibitory control was examined.

5.6.2. Enhancing Inhibitory Control

Inhibitory control was recorded for each of the four tasks for each group. The findings are presented in Table 5.16 below

The results for the EM task showed a significant difference for EM pairs one, two and three. For EM pair one, the higher mean inhibitory control value for the second task shows that inhibitory control was significantly enhanced within the first session. Also, it is seen that there is a huge mean difference between task one and task four (EM pair three), indicating that participants experienced a significant increase in inhibitory control over the two sessions. However, although there was an increase in the level of inhibitory control for EM task four in comparison to task three and task two, the results are not statistically significant. This indicates that as training increased, it became difficult to experience significantly higher levels of inhibitory control. Nonetheless, the three were consistent in their increase, indicating that further training will continue to enhance the level of inhibitory control.

For the DM task on inhibitory control, only DM pair three showed a significant difference. This pair compared the first DM task (session one) with the last DM task (session two). This shows that over the two sessions there was a significant increase in the participant’s level of inhibitory control. The other DM pairs also showed increases in the level of inhibitory control, although the changes were not significant.

Table 5.16: Paired Sample T-test for Inhibitory Control

	N	**Mean Inhibitory Control Values**				**T-test for equality of means**			95% Confidence Interval of the Mean Difference	
Pairs (P)		***1st Task***	***2nd Task***	***3rd Task***	***4th Task***	***Mean Diff.***	***T-Value***	***P-Value***	***Lower***	***Upper***
Panel A: Level One Game Play Across the Two Sessions										
EM One	36	32.25	40.32	-	-	-8.07	-2.874	0.007**	-13.76	-2.37
EM Two	33	26.57	-	37.65	-	-11.09	-2.351	0.028*	-20.87	-1.31
EM Three	33	26.57	-	-	42.26	-15.70	-3.322	0.003*	-25.49	-5.90
EM Four	33	-	32.97	37.65	-	-4.48	-0.982	0.337	-14.56	5.20
EM Five	33	-	32.97	-	42.26	-9.29	-1.751	0.094	-20.29	1.71
EM Six	33			37.65	42.26	-4.61	-0.961	0.347	-14.55	5.34
Panel B: Level Five Game Play Across the Two Sessions										
DM One	36	30.28	33.31	-	-	-3.03	-1.352	0.185	-7.58	1.52
DM Two	33	26.78	-	30.70	-	-3.91	-0.838	0.411	-13.59	5.77
DM Three	33	26.78	-	-	42.26	-15.48	-3.375	0.003**	-24.99	-5.97
DM Four	33	-	28.52	30.70	-	-2.17	-0.493	0.627	-11.33	6.98
DM Five	33	-	28.52	-	37.04	-8.52	-1.510	0.145	-20.23	3.19
DM Six	33	-	-	30.70	37.04	-6.35	-1.453	0.160	-15.41	2.71

$^{**}p < 0.01$; $^{*}p < 0.05$

During the DM task, the participants engaged in difficult mathematics exercises which probably affected their ability to fully evoke the required cognitive actions during the stop signal. This possibly explained why there were more significant differences for the EM task. Nonetheless, looking at both the EM and DM tasks, is can be seen that for both cases there was a significant increase in inhibitory control from the start of session one to the end of session two. This indicates that the BCI Math-Mind game can be used to significantly train and enhance inhibitory control. The findings also support the views of prior studies (Ray *et al.*, 2006; Verbruggen & Logan, 2008) using the stop signal task to train inhibitory control. Also, this study brings a novel approach by using a BCI-based stop signal task. The next cognitive function examined was math anxiety.

5.6.3. Enhancing Math Anxiety

Math anxiety was recorded for each of the four tasks for each group. The findings are presented in Table 5.17 below.

Pair EM one shows a significant difference in math anxiety for the first two attempts of the EM task during the first session. The mean math anxiety for the second attempt is significantly smaller than the first attempt, indicating that the participants successfully improved their math anxiety levels during the first session. Similar significant differences were also observed when comparing the first EM task with the EM task in the second session (pair EM two and EM three). There was, however, no significant difference between the last EM task of session one and the first EM task of session two. This shows that no gain in math anxiety occurs in the time period between the tasks. However, the participants still maintained a comparably good level of math anxiety compared to their first attempt. This shows that the math anxiety training that the participant acquired during the first session remained intact until the second session.

Looking at the DM task, it is seen that the only pair with no significant difference is pair DM four which compared the last DM attempt in session one to the first DM attempt in session two. Similar to the EM task, the participants successfully maintained the trained level of working memory from the first session to the second session. The huge significant difference between the first DM attempt in session one and the last DM attempt in session two indicated that math anxiety can indeed be trained with a BCI-based solution.

Table 5.17: Paired Sample T-test for Math Anxiety

	N	**Mean Anxiety Values**				**T-test for equality of means**			**95% Confidence Interval of the Mean Difference**	
Pairs (P)		***1st Task***	***2nd Task***	***3rd Task***	***4th Task***	***Mean Diff.***	***T-Value***	***P-Value***	***Lower***	***Upper***
Panel A: Level One Game Play Across the Two Sessions										
EM One	36	52.75	27.81			24.94	6.512	0.000**	17.16	32.71
EM Two	33	51.79	-	36.00		15.78	2.804	0.008**	4.32	27.25
EM Three	33	51.79			19.22	32.56	6.194	0.000**	21.85	43.27
EM Four	33		27.03	36.00		-8.97	-1.548	0.131	-20.78	2.83
EM Five	33		27.03		19.22	7.80	1.758	0.088	-1.23	16.84
EM Six	33			36.00	19.22	16.78	4.451	0.000**	9.09	24.45
Panel B: Level Five Game Play Across the Two Sessions										
DM One	36	46.21	28.83			17.38	5.780	0.000**	11.37	23.38
DM Two	33	46.29		32.46		13.83	2.754	0.009**	3.60	24.07
DM Three	33	46.29			16.65	29.65	6.034	0.000**	19.64	39.66
DM Four	33		28.97	32.46		-3.48	-0.903	0.373	-11.33	4.37
DM Five	33		28.97		16.65	12.33	3.901	0.000**	5.89	18.77
DM Six	33			32.46	16.65	15.81	5.567	0.000**	10.14	21.49

$**p < 0.01$; $* p < 0.05$

Based on all the above comparisons, it can be stated that neuro-feedback from the BCI on real time physiological arousal can be used to train learners in controlling and reducing their level of math anxiety. The findings also support prior studies (Gresham, 2007; Hendel & Davis, 1978; Tooke & Lindstrom, 1998; Karimi and Venkatesan, 2009; Scneider and Nevid, 1993; Sharp *et al.*, 2000) which highlighted that math anxiety can be controlled and reduced. The next cognitive function examined is number sense.

5.6.4. Number Sense

Unlike the other three cognitive functions (working memory, inhibitory control, and math anxiety) that were measured with each task, there was a separate task for measuring number sense, as indicated in the protocol (see Section 4.8.2). This task was necessary because number sense deals with "the ability to approximate numerical magnitudes" (Siegler & Booth, 2005 pp. 207) as opposed to providing carefully thought-out answers to questions as used in the BCI Math-Mind game. These carefully thought-out questions of the game provides a basis for enhancing number sense by increasing the game player's understanding of numerical operations as desired for number sense (Reys & Reys, 2009; Sengul, 2013). However, to measure the number sense, a separate specialized task that focused on numerical approximations was most appropriate. The participant's number sense was measured on one occasion in the first session and on one occasion in the second session. A paired sample t-test was used to compare the two measures and the findings are presented in Table 5.18 below.

The number sense pair compared the participant's level of number sense across the two sessions. The results indicated that the number sense level recorded in the second session was significantly higher than the number sense level recorded in the first session. This indicates that there was a significant improvement in the participant's level on number sense across the two sessions. These findings are congruent with recent empirical evidence (Faulkner & Cain, 2013; Park &

Brannon, 2014) which suggest that number sense can be developed and improved. This concludes the section on training cognitive functions. A summary of the key findings are provided in subsection 5.6.5 below.

Table 5.18: Paired sample T-test for Number Sense

	N	**Mean Number Sense Values**		**T-test for equality of means**			**95% Confidence Interval of the Mean Difference**	
Pairs (P)		***Session One Number Sense***	***Session Two Number Sense***	***Mean Diff.***	***T-Value***	***P-Value***	***Lower***	***Upper***
Panel A: Level One Game Play Across the Two Sessions								
Number Sense	33	60.42	79.51	-19.09	-7.018	0.000**	-24.63	-13.55

$^{**}p < 0.01$

5.6.5. Summary on Training Cognitive Functions

Based on the analysis and discussion of results in section 5.6.1, 5.6.2, 5.6.3, and 5.6.4 there was significant evidence to suggest that the Math-Mind BCI-based system could be used to effectively enhance the four selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense). The next section examines the captured brain activity during the task.

5.7. Examining Brain Activity during the Task

In this section, the brain activity (Delta, Theta, Alpha, Beta, and Gamma) captured with the Emotiv Testbench is analysed for each task to determine dominant patterns in brain activity. As previously indicated (Figure 2.5) the Emotiv EPOC BCI has 14 sensors that capture brain activity from the user. During the tasks, brain activity was captured from all 14 channels using the Emotiv Test Bench and extracted to a CSV file that was imported for analysis using EDF Browser and EEGLAB. The subsections below provide the analysis for brain activity during session one for all the 36 participants that took part in the study. It should be noted that the goal was to identify *dominant* brain patterns during the mathematics and cognitive function tasks rather than compare brain activity across sessions. The findings are presented in the subsections below.

5.7.1. Determining the Dominant Brain Activity

The first part looks at the overall patterns in brain activity from the 14 Emotiv EPOC channels for each of the four tasks in the first session.

5.7.1.1. Task One Brain Activity

The results for task one's (T1) brain activity are presented in Figure 5.8 below. The results showed that Delta was the dominant brain pattern across all 14 Emotiv EPOC channels. It was also seen that the magnitude of the Delta power varied across the different channels. Channel F8 showed the highest Delta power followed by channel O2 and F7. Channels F8 and O2 are found in the right sections of the brain indicating dominant brain activity over the right brain hemisphere. The second dominant brain activity was Theta, while the third was Alpha. The Beta and Gamma brain activities where fourth and fifth respectively. Similar to the Delta power pattern, the magnitude of the other brain activities also varied across the different Emotiv EPOC channels. These findings confirm prior studies results (Basar *et al.*, 2001; Onnela, Saramaki, Kertesz & Kaski, 2005; Harmony *et al.*, 1999; Dimitriadis, Laskaris, Tsirka, Vourkas & Micheloyannis, 2010) that have identified increased Delta brain activity during mathematical activities and cognitive functions.

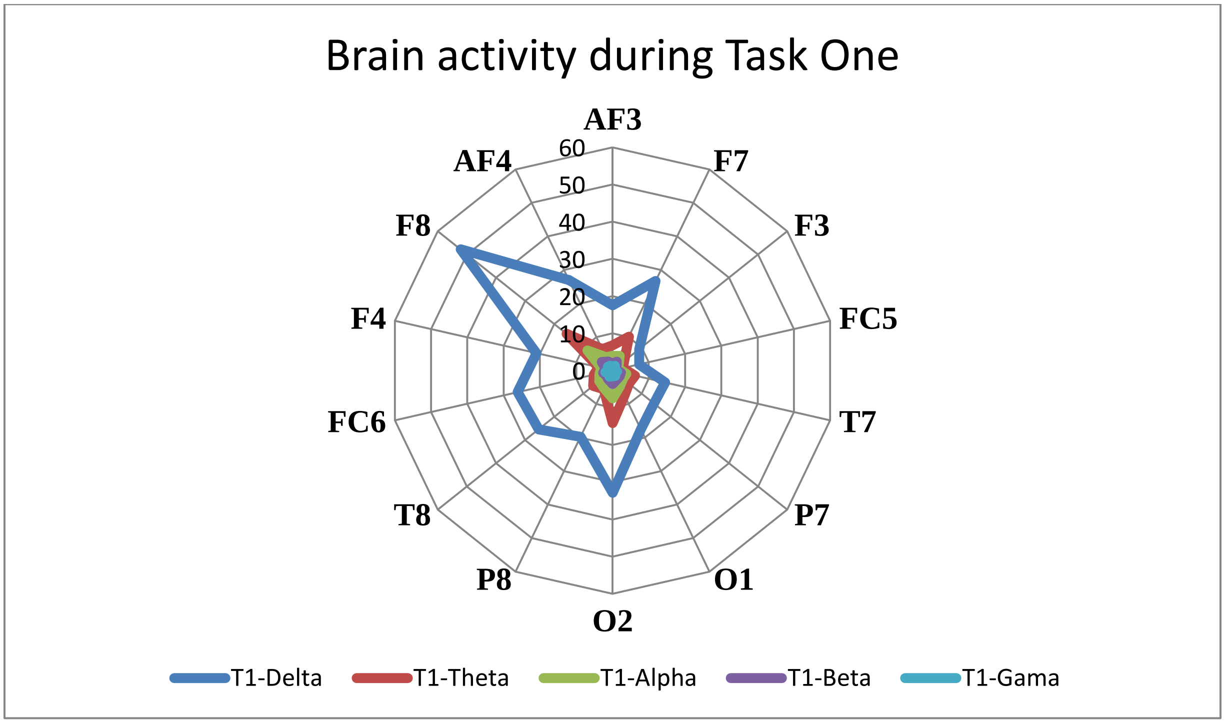


Figure 5.8: Brain Activity during Task One

Also, the second dominant brain activity (Theta) has been widely known to significantly increase during cognitive tasks, especially in the case of working memory (Awang *et al.*, 2011; Rodriguez-Martinez, 2013; Sauseng & Klimesch, 2008; Sauseng, Klimesch, Schabus & Doppelmay, 2005). Gamma brain activity, which achieved the lowest power, is known to be prominent during meditation (Lutz *et al.*, 2004; Vialatte *et al.*, 2009). As such, given the active nature of the task, it seems plausible for the Gamma brain activity to have the lowest power. Next, brain activity during task two was examined.

5.7.1.2. Task Two Brain Activity

The results for task two's (T2) brain activities are presented in Figure 5.9 below. Similar to task one's brain activity, Delta was the dominant brain activity, followed by Theta and Alpha respectively. The fourth dominant brain activity was Beta and the least dominant was Gamma. The pattern is similar to task one, except for the fact that the magnitude of the brain activity varied across the 14 Emotiv EPOC channels. For example, Delta brain activity was the highest in channel F7 as opposed to channel F8 for task one. This indicates more Delta brain activity shifting to the left brain hemisphere for the DM task as opposed to the right hemisphere for the EM task.

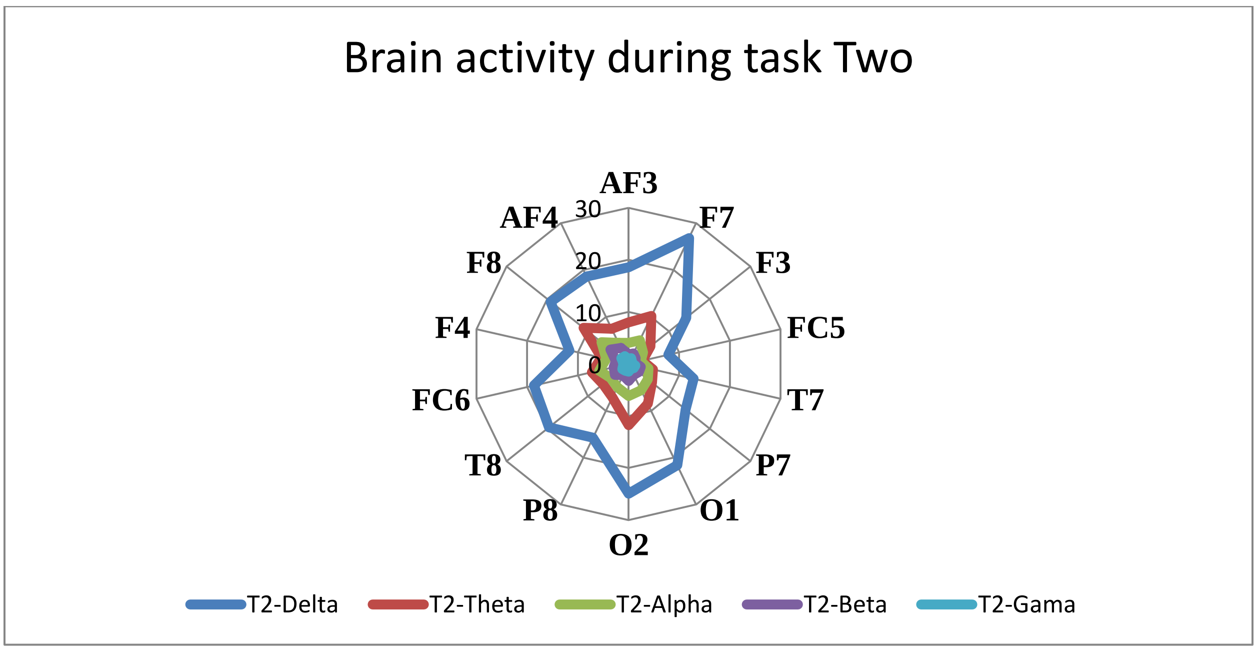


Figure 5.9: Brain Activity during Task Two

Task one involved the easy mathematics exercises and task two the more difficult ones. The changes in brain activity power for the two could possibly be explained by prior studies (Klados *et al.*, 2013; McGraw, Liederman, Johnsen, Lincoln & Frye, 2013; Simos *et al.*, 2011) which highlighted that brain activity changed with mathematics difficulty. This relationship will be further examined in section 5.7.2 below. Next, brain activity during task three will be examined.

5.7.1.3. Task Three Brain Activity

The results for task three's (T3) brain activities are presented in Figure 5.10 below. The dominant brain frequencies in task three were similar to the patterns in task one and two, with the only difference being the magnitude of each brain activity across the 14 Emotiv EPOC channels. Next, the brain activity for task four will be examined.

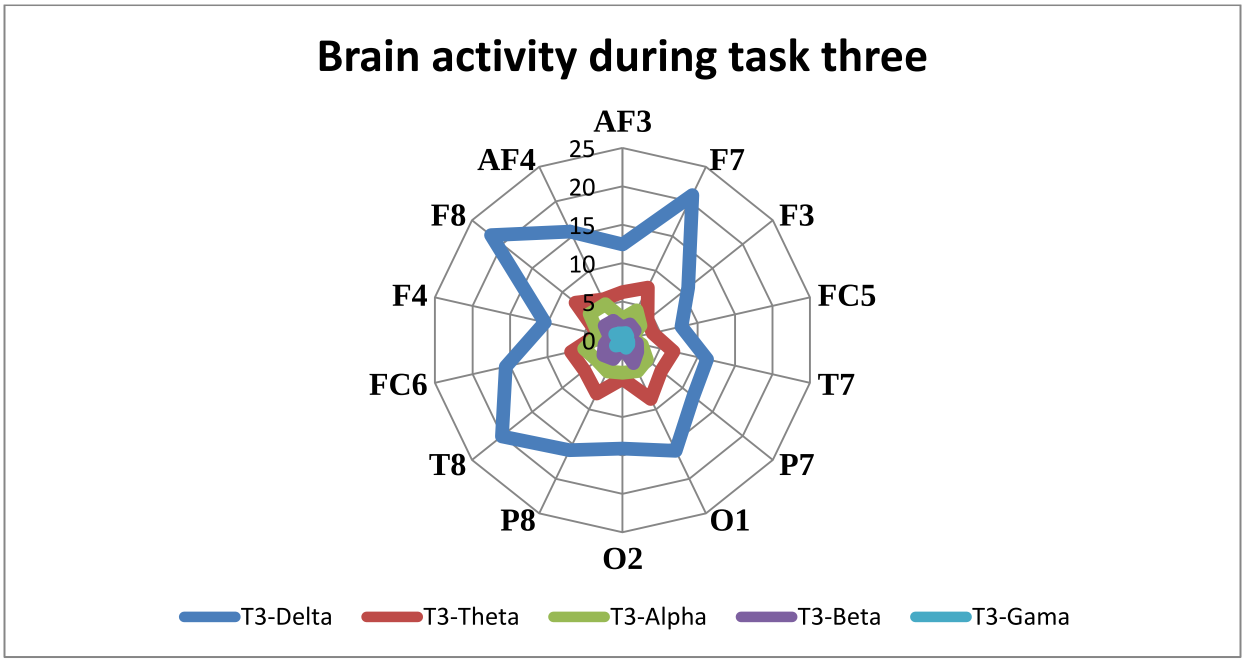


Figure 5.10: Brain Activity during Task Three

5.7.1.4. Task Four Brain Activity

The results for task four's (T4) brain activities are presented in Figure 5.11 below. The dominant brain frequencies in task four were similar to the patterns observed in task one, two, and three, with again the only difference being the magnitude of each brain activity across the 14 Emotiv EPOC channels. The summary of the dominant brain activities is presented below.

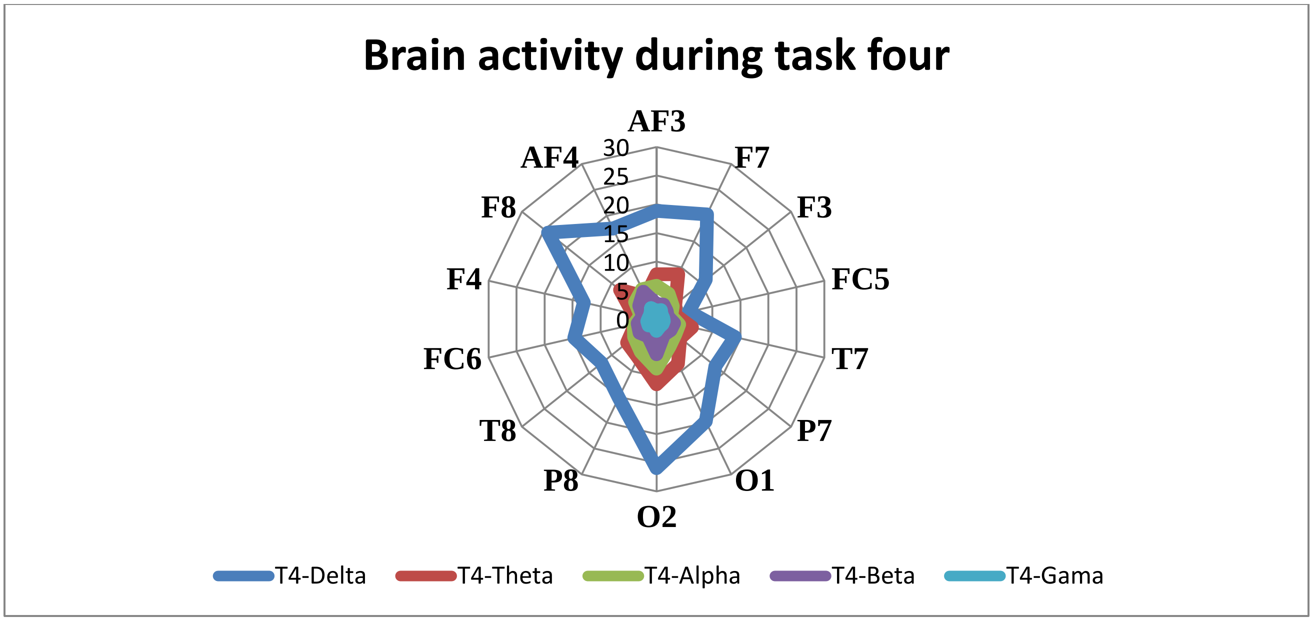


Figure 5.11: Brain Activity during Task Four

5.7.1.5. Summary on Determining Dominant Brain Activity

Based on the observations across the four tasks, it can be concluded that Delta was the dominant brain activity. These results are expected as Baser et al. (2001) highlights that Delta brain wave frequency significantly increases during cognitive functions. The second dominant brain activity was Theta, and the third was Alpha. Theta brain waves are also associated with mental task and problem solving (Awang *et al.*, 2011; Kropotuv *et al.*, 2009) possibly explaining the high amplitudes experienced during the testing sessions. Beta and Gamma took the fourth and fifth places respectively. It was observed that even though the magnitude of the brain activities varied across the different channels, the results were consistent across channels and across tasks. Since brain activity patterns were similar across the 14 Emotiv EPOC channels, hereafter, the average brain activity for all channels will be used as opposed to single channels. The next section examines how task difficulty affected the different brain activities.

5.7.2. Comparing Brain Activity across Task Difficulty

During cognitive processes, the brain usually produces different brain wave activities which often vary in magnitude based on the complexity of the cognitive task (Klados *et al.*, 2013; McGraw *et al.*, 2013; Simos *et al.*, 2011). Prior studies have, however, shown mixed results for the same brain activities, with some studies showing decreased activity with task difficulty and other studies again showing the opposite (Gevins, Smith, McEvoy & Yu, 1997; Klados *et al.*, 2013; Lin, Jung, Wu, Lin & She, 2012). To examine this pattern the average brain activity for the EM and DM was compared. The results are presented in Figure 5.12 and Table 5.19 below.

From the results in Figure 5.12 it can be seen that all the brain activities, except for Delta, increased with task difficulty. The findings are congruent with prior studies that identified increases in Theta (Gundel & Wilson, 1992; Gevins *et al.*, 1997; Klados *et al.*, 2013) and Alpha activities (Jensen, Gelfand, Kounios & Lisman, 2002) with increased task difficulty.

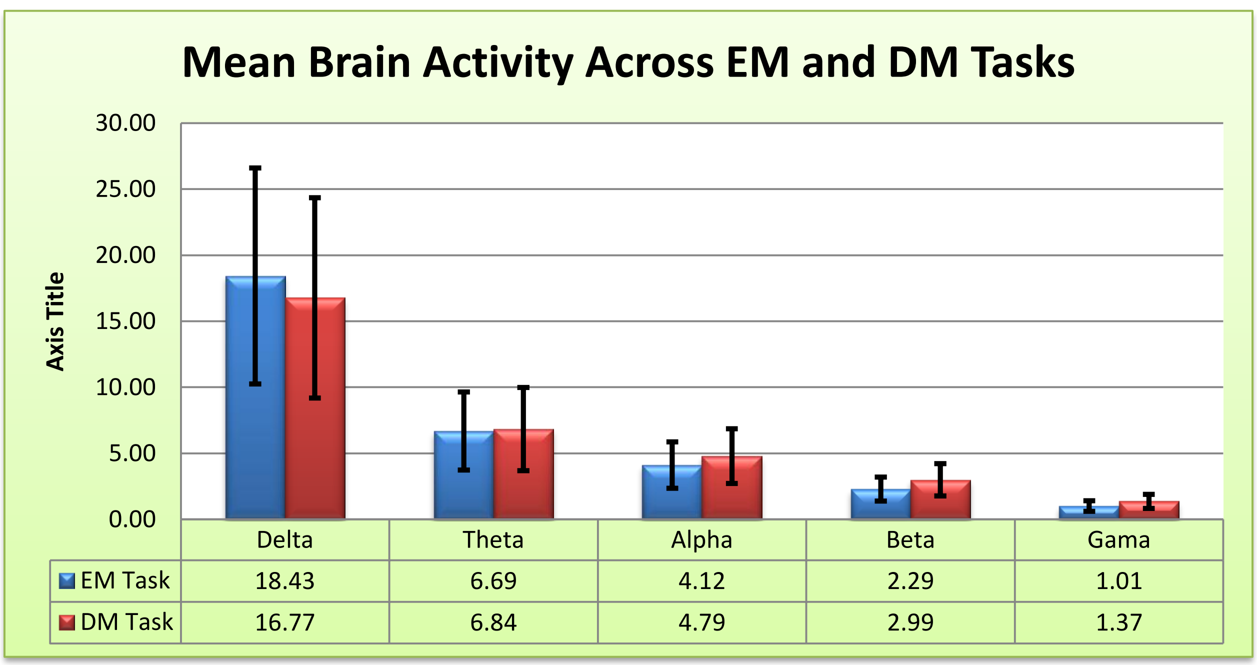


Figure 5.12: Mean Brain Activity across EM and DM Task

The findings, however, contradict prior studies (Lin *et al.*, 2012) that showed a decrease in Theta and Beta brain activity with an increase in task difficulty. In order to determine if the identified differences were significant a paired sample T-test was performed and the results are presented in Table 5.19 below.

Table 5.19: T-Test for comparison of EM and DM task Brain Activity

Brain Activity	Mean Difference	98% Confidence interval of the difference		T-test for equality of Means	
		Lower	Upper	T-Value	P-Value
Delta	1.65	-1.53	4.84	1.053	0.299
Theta	-0.15	-1.04	0.73	-0.356	0.724
Alpha	-0.68	-1.39	0.43	-1.909	0.064
Beta	-0.70	-1.08	-0.33	-3.783	0.001***
Gamma	-1.74	-4.53	-1.26	-1.262	0.215

Based on the results in Table 5.19, only the Alpha brain activity was significantly higher with increased task difficulty. This confirms the findings by Jensen *et al.* (2013) and contradicts that of Lin *et al.* (2013). Another aspect that needs to be considered is the fact that left and right brain hemispheres have been shown to indicate different levels of involvement with mathematics and cognitive functions (Hyungkyu, Jangsik & Eunjung, 2009; Laad, 2013). Hyungkyu *et al.* (2009) also showed that during a complex mathematical task, the activation of Theta activity was significantly different for the left and right brain hemispheres. As such, the next section separates the brain activity into left and right hemispheres and examines the results.

5.7.3. Brain Activity across Left and Right Brain Hemispheres

In order to determine brain activity in the right and left brain hemispheres, the 14 EEG channels from the Emotiv EPOC BCI device must be separated to indicate the different hemispheres from which each channel captures brain activity. Table 5.20 below maps each of the channels to particular regions of the brain.

Table 5.20: Mapping of Emotiv EPOC Channels to Brain Regions

Brain Region	Channels	Corresponding Electrodes
Left hemisphere	1-7	AF3, F7, F3, FC5, T7, P7, O1
Right hemisphere	8-14	O2, P8, T8, FC6, F4, F8, AF4
Entire Brain	1-14	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4

Source: Kuzovkin (2013)

For locations of the corresponding electrodes on the Emotiv EPOC BCI, please refer to Figure 2.5. The results for the left and right brain hemispheres are presented in the subsections below.

5.7.3.1. EM Task Brain Activity for Left and Right Brain Hemispheres

Brain activity during the EM task was compared for the left and right brain hemispheres and the findings are presented in Figure 5.13 and Table 5.21 below.

The results show that for all the brain signals, there was dominant brain activation in the right brain hemisphere. The high activation of brain activity over the right brain hemisphere can be attributed to the fact that the right brain hemisphere is responsible for processing both positive and negative emotions (Borod, Bloom, Brickman, Nakhutina & Curko, 2002) which the participants experienced while performing the different task.

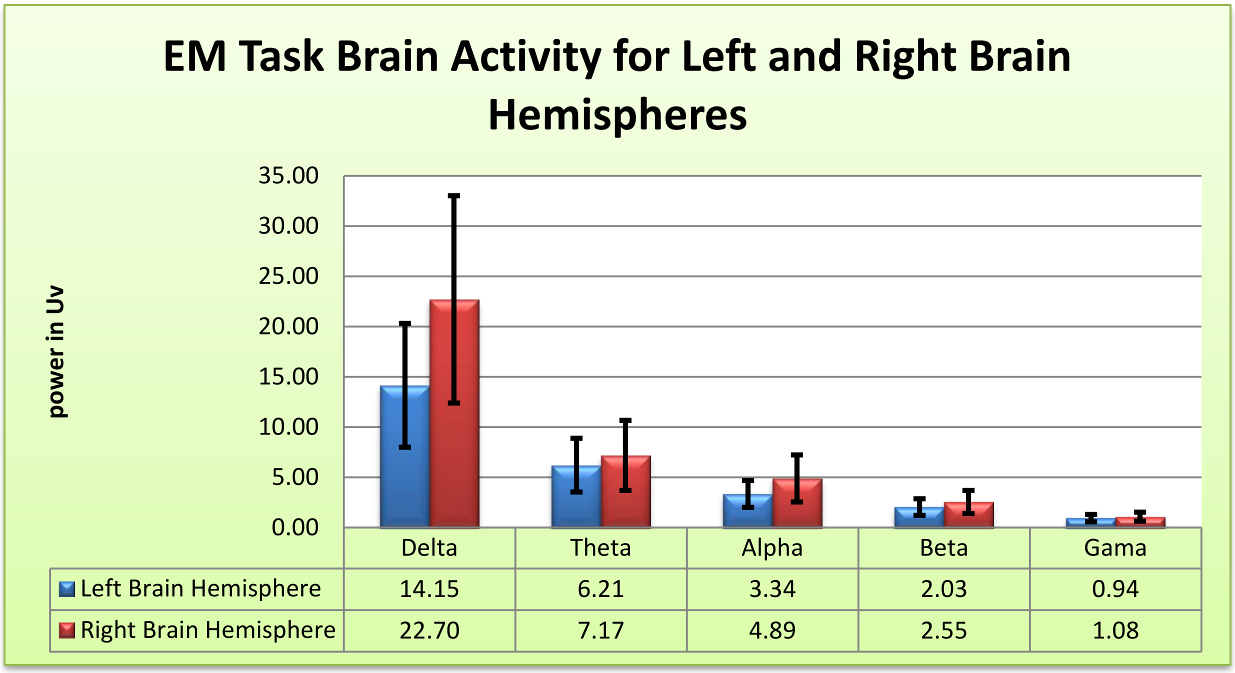


Figure 5.13: EM Task Brain Activity for Left and Right Brain Hemispheres

In order to determine if the identified differences in brain activation for the left and right hemispheres was significant, a T-test was performed (Table 5.21).

Table 5.21: EM Task Brain Activity across Left and Right Hemispheres

Brain Activity	**Mean Difference**	**98% Confidence interval of the difference**		**T-test for equality of Means**	
		Lower	Upper	T-Value	P-Value
Delta	-8.55	-13.22	-3.87	-3.712	0.001***
Theta	-0.96	-2.84	0.92	-1.037	0.307
Alpha	-1.55	-3.01	-0.09	-2.165	0.037**
Beta	-0.51	-1.31	0.29	-1.304	0.201
Gamma	-0.14	-0.41	0.12	-1.096	0.280

The results showed that only the Delta and Alpha differences were significant. This indicates that during easy mathematical tasks there is more activation of Alpha and Delta in the right hemisphere than in the left hemisphere. As mentioned before, Delta has been known to dominate during cognitive functions (Basar *et al.*, 2001) and this probably suggests increased activity for cognitive functions in the right brain hemisphere. Similarly, Alpha waves dominate during consciousness (Sherman *et al.*, 2011) and as such, during math exercises, more consciousness is seen to be applied over the right hemisphere. The next section examines the left and right brain activity during the DM task.

5.7.3.2. DM Task Brain Activity for Left and Right Brain Hemispheres

Brain activity during the DM task was compared for the left and right brain hemispheres and the findings are presented in Figure 5.14 and Table 5.22 below.

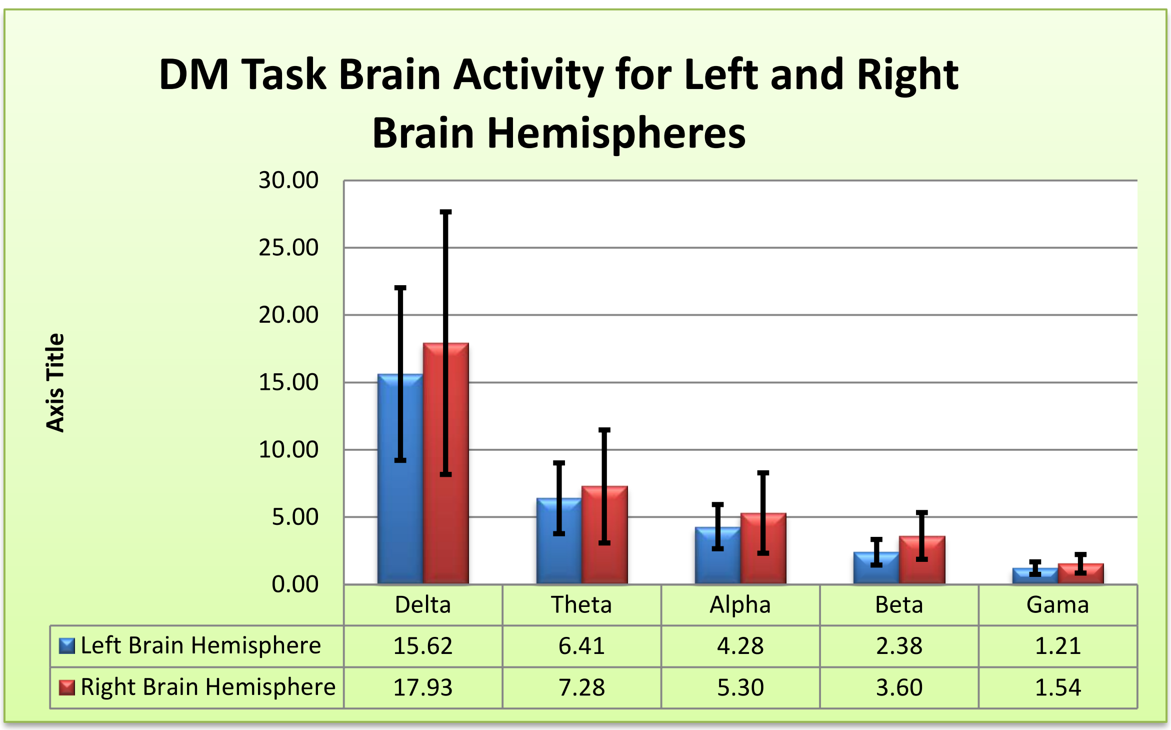


Figure 5.14: DM Task Brain Activity for Left and Right Brain Hemispheres

Similar to the EM task, all the brain activities were dominant over the right hemisphere. The significance of the observed differences is depicted in Table 5.22 below.

Table 5.22: DM Task Brain Activity across Left and Right Hemispheres

Brain Activity	Mean Difference	98% Confidence interval of the difference		T-test for equality of Means	
		Lower	Upper	T-Value	P-Value
Delta	-2.30	-8.82	4.21	-0.718	0.477
Theta	-0.87	-3.96	2.19	-0.579	0.566
Alpha	-1.02	-3.46	1.41	-0.852	0.400
Beta	-1.21	-2.61	0.18	-1.768	0.086
Gamma	-3.08	-8.67	2.51	-1.119	0.217

The results showed that there was no significant difference in brain activity over the left and right brain hemispheres. This suggests that with task difficulty, the brain activates both regions in an almost equal manner. As such, based on these findings, the debate on left and right brain activity still remains inconclusive as explicated by Weiten (2013). While there are no significant differences between the left and right brain for the DM task, it is imperative to examine if brain activity increases with task difficulty within each brain hemisphere. The findings are presented in the next subsection.

5.7.3.3. Comparison of Hemispheric Brain Activation across Math Difficulties

Using a paired sample t-test, the brain activities for each hemisphere across task difficulty were compared. These findings are presented below (Table 5.23). The findings showed that there was a significant increase in Alpha, Beta and Gamma brain waves over the left hemisphere and in Beta waves over the right hemisphere as task difficulty increased.

The increase in Beta wave power for both hemispheres with task difficult is contrary to the findings of Lin *et al.* (2013). However, Howells, Stein and Russell (2010) showed that during the stop signal task, there was increased Beta activity with increase in task difficulty. Given that the

BCI-based stop signal task was incorporated in all the tasks, it possibly explains the significant increases in Beta activity with task difficulty.

Table 5.23: Comparison of Hemispheric Brain Activity across Task Difficulty

Brain Activity	**Mean Difference**	**98% Confidence interval of the difference**		**T-test for equality of Means**	
		Lower	Upper	T-Value	P-Value
Left Hemisphere					
Delta	-1.47	-3.11	0.17	-1.821	0.077
Theta	-0.19	-0.91	0.52	-0.556	0.582
Alpha	-0.94	-1.54	-0.34	-3.195	0.003***
Beta	-0.35	-0.58	-0.13	-3.208	0.003***
Gamma	-0.27	-0.43	-0.11	-3.552	0.001***
Right Hemisphere					
Delta	4.77	-0.79	10.341	1.740	0.091
Theta	-0.11	-1069	1.46	-0.146	0.885
Alpha	-0.41	-1.70	0.88	-0.651	0.520
Beta	-1.05	-1.74	-0.37	-3.133	0.003***
Gamma	-3.21	-8.79	2.38	-1.166	0.251

***p<0.01

Differences in brain activation in the left and right hemispheres can also be accounted for by demographic factors (Kohei *et al.*, 2014; Nielsen, Zielinski, Ferguson, Lainhart & Anderson, 2013; Šveljo, Koprivšek, Lucic, Prvulovic & Culic, 2010). In this regard, patterns in brain activity across hemispheres were examined based on gender and the findings are presented in the next subsection.

5.7.3.4. Examine Brain Activity by Demographic Factors

A Pearson correlation analysis was performed to determine the relationship between demographic factors and brain activity during EM and DM tasks. The results are presented in Table 5.24 below

Table 5.24: Relationships between Demographic Factors and Brain Activity

	Gender	Age	Educational Level
Left Hemisphere EM Task			
Delta	0.334**	-0.267	-0.285**
Theta	0.314**	-0.245	-0.238
Alpha	0.300**	-0.228	-0.219
Beta	0.248	-0.256	-0.279
Gamma	0.302**	-0.290**	-0.291**
Right Hemisphere EM task			
Delta	0.376***	-0.241	-0.256
Theta	0.315**	-0.033	-0.072
Alpha	0.319**	-0.004	-0.053
Beta	0.185	-0.001	-0.018
Gamma	0.289**	-0.041	-0.116
Left Hemisphere DM Task			
Delta	0.302**	-0.139	-0.179
Theta	0.266	-0.121	-0.144
Alpha	0.244	-0.109	-0.219
Beta	0.212	-0.191	-0.231
Gamma	0.277	-0.160	-0.202
Right Hemisphere DM Task			
Delta	0.323**	0.020	-0.005
Theta	0.326**	-0.001	-0.016
Alpha	0.272	0.045	0.020
Beta	0.124	-0.001	0.018
Gamma	0.192	-0.102	-0.114

***p<0.01; **p<0.05

For gender, the results showed a significant positive relationship to Delta, Theta, Alpha and Gamma for both the left and right hemispheres during the EM task. This indicates that for these brain activities females tend to have a significantly higher level of activation compared to males during EM tasks. However, as task difficulty increased, only the Delta brain activity was significant for the left hemisphere and the Delta and Theta brain activities for the right hemisphere.

For age, the only significant relationship seen was an inverse relationship to Gamma brain activity in the left hemisphere during the EM task. This indicates that during easy mathematical exercises, younger participants tend to portray a higher activation of Gamma power than older participnats.

Education showed a significant negative relationship to Delta and Gamma brain activities during the EM task. Similar to the findings for age, this depicted that as the education level increased, Delta and Gamma brain activity were less required during easy mathematical exercises.

5.7.3.5. Summary on Brain Activity during Tasks

This section examined how brain activity differs across the left and right brain hemispheres in respect to task difficulty. For the EM task, the results showed significant increases in Alpha and Delta brain activity over the right hemisphere. However, there were no significant differences in hemispheric brain activity during the DM task. Comparing the left and right brain hemispheres showed that Beta brain activity increased across both hemispheres with task difficulty, while Alpha and Gamma increased over the left hemisphere. The information presented in this section is vital in depicting the context of which the study was based as the elicited brain activity could significantly vary based on the difficulty level of the game and demographic factors. Understanding this is vital for contextualizing the results in the next section which address a key the results in the next section relating to hypothesis two of this study. Next, the relationship between brain activity and cognitive functions will be examined.

5.7.4. Relationship between Brain Activity and Cognitive Functions

A Pearson correlation analysis was performed to determine the relationship between cognitive functions and brain activity. The results are presented in Table 5.25 below. Math anxiety showed a statistically significant positive relationship to Gamma brain activity over the left brain hemisphere for the DM task. This indicated that increases in Gamma brain activity were associated with increased levels of math anxiety.

Table 5.25: Relationship between Cognitive Functions and Brain Activity

	Math Anxiety	Inhibitory Control	Working Memory	Number Sense
Left Hemisphere EM Task				
Delta	0.111	-0.276	-0.349**	0.027
Theta	0.051	-0.214	-0.236	0.029
Alpha	0.031	-0.179	-0.216	0.027
Beta	0.106	-0.249	0.357**	-0.035
Gamma	0.065	-0.299**	-0.307**	0.005
Right Hemisphere EM Task				
Delta	0.068	-0.309**	-0.286**	0.098
Theta	0.061	-0.205	-0.061	0.180
Alpha	0.031	-0.168	-0.025	0.190
Beta	0.093	-0.120	-0.075	0.076
Gamma	0.200	-0.237	-0.162	0.056
Left Hemisphere DM Task				
Delta	0.276	-0.137	-0.199	0.043
Theta	0.227	-0.121	-0.141	0.057
Alpha	0.173	-0.079	-0.114	0.009
Beta	0.262	-0.155	0.304**	-0.018
Gamma	0.315**	-0.172	-0.256	0.005
Right Hemisphere DM Task				
Delta	0.152	0.009	0.060	0.216
Theta	0.106	0.011	0.057	0.214
Alpha	0.019	0.072	0.107	0.342**
Beta	0.149	-0.100	0.026	0.109
Gamma	-0.208	-0.65	0.131	0.222

**p<0.05

This finding is congruent with evidence by Oathes *et al.* (2008) which showed that high anxiety levels were significantly correlated with higher increases in Gamma brain activity. Similarly, Albrecht, Çalışkan, Oitzl, Heinemann and Stork (2013) observed related patterns by showing that reduced Gamma oscillation resulted in reduction of anxiety-like behaviour. Existing evidence (Gruber & Muller, 2002) suggests that Gamma activity can be reduced with recurrent presentation of the same visual stimulus. It has also been noted that this reduction in Gamma activity results in improved perception of the stimulus (Moldakarimov, Bazhenov & Sejnowski, 2010). Since an increase in Gamma activity is associated with increased math anxiety, it can be suggested that continuous exposure to mathematical exercises will result in reduced math anxiety and improved perception of the mathematical concepts. This supports the view that math anxiety can be reduced through continuous learning of mathematics (Jansen *et al.,* 2013).

Inhibitory control showed a negative relationship to Gamma brain activity over the left hemisphere for the EM task and Delta activity over the right hemisphere for the EM task. The results are in line with the findings of Schiller, Gianotti, Nash & Knoch (2014) who indicated a negative relationship between Delta brain activity and inhibitory control. Similarly Choi *et al.* (2013) established that people with high Gamma brain activity portrayed low levels of inhibitory control.

Working memory showed a statistically significant relationship to Delta, Beta and Gamma waves over the left hemisphere for the EM task. Working memory also showed a statistically significant relationship to Delta over the right hemisphere for the EM task and Beta over the left hemisphere for the DM task. The consistent positive relationship between Beta brain activity over the left hemisphere and working memory is congruent with prior studies (Altamura *et al.,* 2010; Roberts, Hsieh & Ranganath, 2013) which showed that Beta power increased in the left brain hemisphere during working memory tasks. Similarly, without specifying specific regions of the brain, Zanto and Gazzaley (2009) established that Beta oscillations increased with higher performance of working memory. Furthermore, this study failed to find a significant relationship between Theta brain waves and working memory as prior evidence has suggested (Heister *et al.*, 2013; Kawasaki & Yamaguchi, 2013). However, this significant relationship between Theta and working memory has been identified specifically for visuospatial working memory (Heister *et al.*, 2013; Kawasaki & Yamaguchi, 2013). Following from the results in Section 5.5.1.2., it can be seen that the BCI-measured working memory was not related to visuospatial working memory, but only to the central executive working memory and storage working memory. As such, it is plausible to find no significant relationship between Theta brain activity and the BCI-measured working memory. On another note, the significant negative relationship between Gamma brain activity and working memory continues to indicate the negative influence of Gamma brain activity on cognitive functions.

For inhibitory control, it was seen that only the Alpha brain activity over the right hemisphere for the DM task had a positive statistically significant relationship to inhibitory control. This supports existing evidence that Alpha brain waves play an active role in inhibitory control (Hwang, Ghuman, Manoach, Jones & Luna, 2014; Klimesch, Sauseng & Hanslmayr, 2007; Sauseng, Gerloff & Hummel, 2013). Likewise, Romei, Gross and Thut, (2012) observed increased Alpha brain activity during inhibitory control tasks.

This concludes the section on examining brain activity with respect to task difficulty and cognitive functions. The next section examines the affective states and their relationship to cognitive functions and mathematics performance.

5.8. Examining Affective States

Affective states have been known to play an importantt role in fostering cognitive functions as well as having an impact on learning (Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009). Empirical evidence indicates that positive emotions such as engagement and concentration can enhance learning (Kanfer & Ackerman, 1989; Pekrun, Goetz, Titz & Perry, 2002; Sabourin & Lester, 2014), while negative emotions such as frustration, anxiety, and boredom have an adverse effect on learning (Meyer & Turner, 2006; Sabourin & Lester, 2014). Using the Affectiv Suite of the EMotiv EPOC BCI device, four affective states were captured, namely: engagement, meditation, frustration, and long-term excitement. Of these four affective states, engagement and meditation are considerd as positive emotions (Fredrickson, Cohn, Coffey, Pek & Finkel, 2008; Pekrun *et al.*, 2002; Sabourin & Lester, 2014), while frustration and long term excitement are considered negative emotions (Brooks, 2014; Meyer & Turner, 2006; Sabourin & Lester, 2014). There are also situations in which excitement can be considered a positive emotion, especially when the excitement results from a positive experience (Brooks, 2014; Jamieson, Mendes, Blackstock & Schmader, 2010). Nontheless, excitement and anxiety have similar experiences and based on the situation in which the data was captured, it seemed more likely to group excitement as a negative emotion (anxiety) as it was likely induced by fear of the mathematics exercises. Excitement becomes anxiety when it focuses on negative consequences (Brooks, 2014; Jamieson, Mendes & Nock, 2013). It should be noted that instantaneos excitement was left out because it had been incorporated in the BCI Math-Mind game as a measure of physiological arousal for monitoring math anxiety.

5.8.1. Affective States Across Levels of Task Difficulty

The affective states for all players were captured for the entire task and the results are presented based on task difficulty. The Emotiv EPOC BCI device captured the affective states on a scale of zero to one. The data was then transformed to a 100% scale and the findings presented in Figure 5.15 below.

Generally, high positive affective states (engagement and meditation) are good while the opposite is true for negative affective states (frustration and long-term excitement). For the positive affective states, engagement values were higher than meditation values. This seems plausible as participants were more likely to use the emotion of engagement rather than meditation during mathematics exercises.

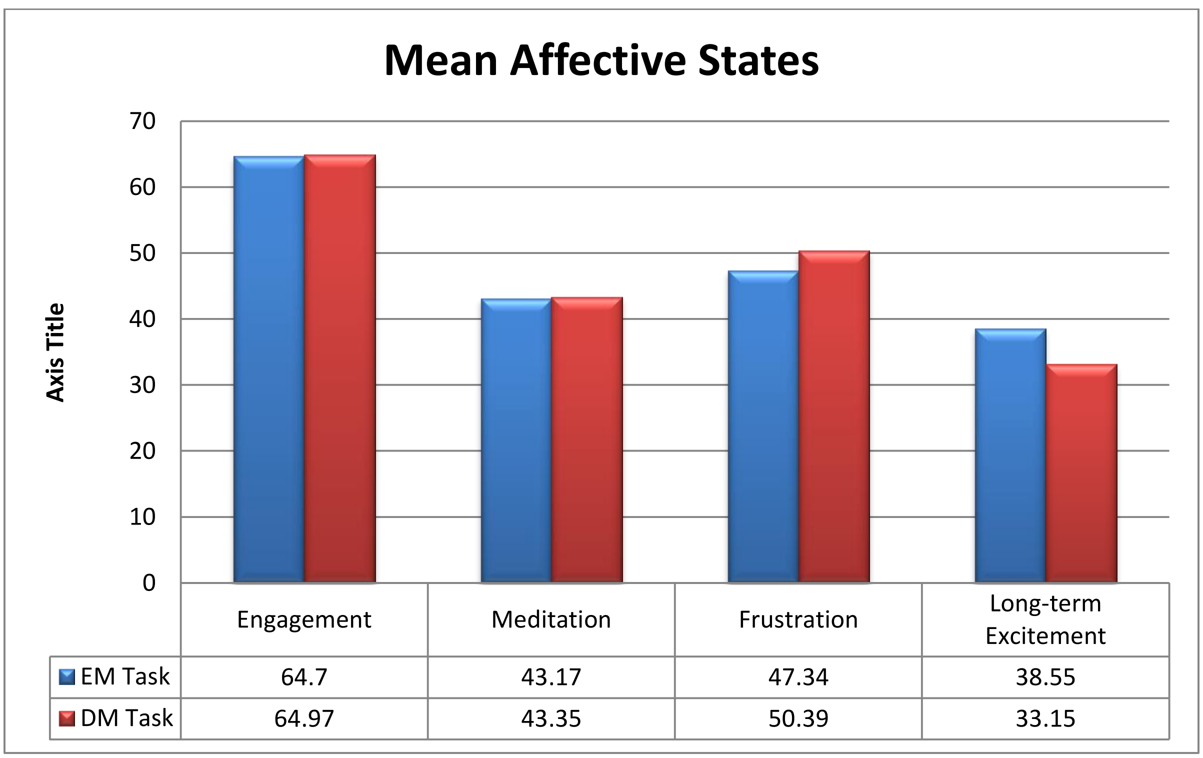


Figure 5.15: Affective States across Task Difficulties

For the negative affective states, long-term excitement was lower compared to frustration. The results also indicate that there were slight differences in affective states across the two levels of task difficulty. In order to examine if the differences were significant, a T-test analysis was performed and the findings are reported in Table 5.26

The findings showed that there was no significant difference in affective states across task difficulty. As such, this study was unable to establish whether or not task difficulty affects affective states.

Table 5.26: Comparison of Affective States across Task Difficulty

Affective States	**Mean Differenc e**	**98% Confidence interval of the difference**		**T-test for equality of Means**	
		Lower	**Upper**	**T-Value**	**P-Value**
Engagement	-0.27	-2.34	1.79	-0.269	0.790
Meditation	-0.18	-1.25	0.89	-0.342	0.735
Frustration	-3.05	-10.81	4.71	-0.798	0.430
Long-term Excitement	5.40	-0.54	11.33	-1.845	0.074

The next step was to examine if affective states had a significant impact on cognitive functions. Prior studies (Garcia-Molina, Tsoneva & Nijholt, 2013; Pell, Monetta, Rothermich, Kotz, Cheang & McDonald, 2014) have highlighted key dependencies between affective and cognitive states. The findings are presented in section 5.8.2 below.

5.8.2. Affective States and Cognitive Functions

This section presents the relationship between affective states and cognitive functions. The results in the subsections below explain how affective states affect each of the four cognitive functions.

5.8.2.1. Affective States and Working Memory

A linear regression analysis was performed to determine how affective states impacted on working memory and the findings are presented in Table 5.27 below. The F-values for both models were significant showing that the overall models were statistically significant. With regards to the specific affective states, it was seen that engagement had a positive and statistically significant influence on working memory across the two models.

The findings are in line with existing studies (Awh, Vogel & Oh, 2006; Berka *et al.*, 2007; Park *et al.*, 2014) which portrayed that working memory capacity is dependent on the person's level of engagement on the task. The other affective states showed no significant relationship to working memory.

Table 5.27: Relationship between Affective States and Working Memory

Affective State variables	**Models**					
	Model A			**Model B**		
	Beta	T-Value	P-Value	Beta	T-Value	P-Value
Constant		0.891	0.380		0.931	0.359
Engagement	0.505	3.233	0.003***	0.372	2.328	0.027**
Meditation	0.191	1.326	0.194	-0.110	-0.808	-0.425
Frustration	0.157	1.017	0.317	-0.173	-1.087	-0.286
Long-Term Excitement	-0.272	-1.873	0.071	-0.273	-1.799	0.082

Model Parameters		
R^2	0.376	0.433
Adjusted R^2	0.296	0.359
F-value (sig.)	4.672 (0.005)***	5.909 (0.001)**
Dubin Watson Stat	1.309	1.338

Model A represents the EM task and model B the DM task

**** $p < 0.01$; ** $p < 0.05$*

The next cognitive function examined was inhibitory control.

5.8.2.2. Affective States and Inhibitory Control

A linear regression analysis was performed to determine how affective states impacted on inhibitory control and the findings are presented in Table 5.28 below.

The F-values for Model A was not statistically significant, indicating that affective states did not significantly impact on inhibitory control for the EM task. For the DM task, the F-value was statistically significant showing that the overall model of affective states impacted on inhibitory control. The results for model B showed that meditation had a significant positive influence and long-term excitement had a significant negative influence on inhibitory control. The positive effect of meditation on inhibitory control supports existing evidence that inhibitory control can be enhanced with meditation (Friese, Messner & Schaffner, 2013; Gothe, Pontifex, Hillman & McAuley, 2013).

Table 5.28: Relationship between Affective States and Inhibitory Control

Affective State variables	Models					
	Model A			Model B		
	Beta	T-Value	P-Value	Beta	T-Value	P-Value
Constant		-0.095	0.925		2.342	0.026

Engagement	0.018	0.097	0.924	-0.024	-0.134	0.894
Meditation	0.084	0.492	0.626	0.371	2.421	0.022**
Frustration	0.320	1.740	0.092	0.040	0.221	0.827
Long-Term Excitement	0.048	0.280	0.781	-0.374	-2.189	0.036**
Model Parameters						
R^2		0.117			0.279	
Adjusted R^2		0.003			0.186	
F-value (sig.)		1.030 (0.408)			3.001 (0.033)**	
Dubin Watson Stat		1.136			1.834	

Model A represents the EM task and model B the DM task

**** $p < 0.01$; ** $p < 0.05$*

Furthermore, negative emotions of excitement, which mostly result from fear and anxiety, have been known to significantly impair inhibitory control (Pacheco-Unguetti, Acosta, Lupiáñez, Román & Derakshan, 2011; Padmala, Bauer & Pessoa, 2011; Pessoa, Padmala, Kenzer & Bauer, 2012). This possibly explains the significant negative relationship between long-term excitement and inhibitory control. The next cognitive function examined was math anxiety.

5.8.2.3. Affective States and Math Anxiety

A linear regression analysis was performed to determine the impact of affective states on math anxiety. The findings are presented in Table 5.29 below.

Table 5.29: Relationship between Affective States and Math Anxiety

Affective State variables	**Models**					
	Model A			**Model B**		
	Beta	T-Value	P-Value	Beta	T-Value	P-Value
Constant		1.084	0.287		-0.267	0.791
Engagement	-0.039	-0.303	0.764	0.102	0.887	0.382
Meditation	-0.112	-0.950	0.350	-0.085	-0.865	0.394

Frustration	-0.032	-0.256	0.800	0.237	2.056	0.048**
Long-Term Excitement	0.757	6.352	0.000***	0.763	6.964	0.000***
Model Parameters						
R^2		0.579			0.704	
Adjusted R^2		0.525			0.666	
F-value (sig.)		10.669 (0.000)***			18.459 (0.000)***	
Dubin Watson Stat		1.925			2.018	

Model A represents the EM task and model B the DM task

**** p < 0.01; ** p < 0.05*

The F-values for both models were significant, showing that the overall models were statistically significant. With regards to the specific affective states, it was seen that only long-term excitement had a statistically significant influence on math anxiety across the two models. The strong positive relationship indicates that long-term excitement was highly related to math anxiety. This clearly supports the view of treating long-term excitement as a negative emotion for the purpose of this study. Also, in Model B, frustration showed a significant positive influence on math anxiety. This shows that increases in the level of frustration will result in increased math anxiety. This confirms the views that negative emotions are not good for learning (Meyer & Turner, 2006; Sabourin & Lester, 2014) as the high math anxiety induced by frustration will result in poor mathematics performance. The next cognitive function examined was number sense.

5.8.2.4. Affective States and Number Sense

A linear regression analysis was performed to determine the impact of affective states on inhibitory control. The findings are presented in Table 5.30 below.

Table 5.30: Relationship between Affective States and Number Sense

Affective State variables	Models					
	Model A			Model B		
	Beta	T-Value	P-Value	Beta	T-Value	P-Value
Constant		1.07	0.290		-0.851	0.401
Engagement	-0.321	-1.941	0.061	0.395	2.269	0.030**
Meditation	0.408	2.673	0.012**	0.068	0.458	0.650
Frustration	-0.049	-0.302	0.765	-0.262	-1.509	0.141
Long-Term Excitement	-0.338	-2.200	0.035	0.009	0.055	0.957
Model Parameters						
R^2	0.299			0.328		
Adjusted R^2	0.209			0.241		
F-value (sig.)	3.310 (0.023)**			3.784 (0.013)**		
Dubin Watson Stat	1.453			1.655		

Model A represents the EM task and model B the DM task

**p<0.05

The F-values for both models A and B were significant at the 5% level, indicating the overall significance of both models. For model A, it was seen that only meditation had a statistically significant influence on number sense. In model B, only engagement was observed to have a statistically significant influence on number sense. The positive coefficient indicates that when the level of engagement increased, the level of number sense also increased. The finding is congruent with those of Sood (2010) who also established a positive relationship between engagement and number sense. The next section provides a summary of the findings regarding affective states.

5.8.3. Summary on Examining Affective States

In examining the affective states, it was observed that there were no significant differences in affective states based on task difficulty. When appraising the relationship between affective states and cognitive functions, it was observed that engagement had a statistically significant relationship to working memory and number sense. Meditation had a statistically significant relationship to inhibitory control and number sense. Frustration showed a statistically significant relationship to math anxiety. Long-term excitement showed a statistically significant negative relationship to inhibitory control and a positive relationship to math anxiety. In the next section, the impact of affective states and cognitive functions on mathematics performance was examined.

5.9. Mathematics Performance

Affective states and cognitive functions have been established to have a predictive power on mathematics performance (Alloway & Alloway, 2010; Bull & Scerif, 2001; Espy *et al.,* 2004; Mazzocco *et al.,* 2011; Ponitz *et al.,* 2019; Toll *et al.,* 2011; Witt, 2011; Zakaria *et al.,* 2012). The first relationship examined was that of affective states and mathematics performance.

5.9.1. Affective States and Mathematics Performance

It is known that positive affective states enhance learning, while negative affective states have an adverse effect on learning (Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009). This section examines the impact of the selected affective states on mathematics performance. A regression analysis was performed and the results are presented in Table 5.31 below.

In examining this relationship it was imperative to control for factors that could significantly influence the outcome. As such, two factors (educational level and computer experience) were used as control factors in the regression. This is because it was expected that participants at a higher educational level could perform better in the mathematics exercises because of the learning they have encountered and not because of the affective states captured in the study.

Also, participants with less computer experience might commit errors that are a result of computer competency and not their ability to correctly select the correct answer before the time for a question runs out. For these reasons, these two factors were used as control variables when examining the impact of affective states on mathematics performance, as well as the impact of cognitive functions on mathematics performance.

From the results, it was seen that the F-statistics for both models were statistically significant. Similarly, F-Change for both models was significant, indicating that education and computer experience had a significant influence on the model. Based on the R^2-Change Values, it is seen that these two control variables accounted for 18.7 % of the variance in Model A, and 34.5% in Model B.

Table 5.31: Relationship between Affective States and Mathematics Performance

	Models					
	Model A			**Model B**		
Variables	Beta	T-Stats	(P-Value)	Beta	T-Stats	(*P-Value*)
Constant		0.333	0.741		-2.108	0.045**
Engagement	0.286	2.276	0.030**	0.574	4.325	0.000***
Meditation	-0.046	-0.373	0.712	-0.068	-0.523	0.606
Frustration	-0.415	-3.204	0.003***	-0.042	-0.298	0.768
Long-term Excitement	-0.079	-0.665	0.511	-0.003	-0.019	0.985
Education	-0.094	-0.590	0.559	0.692	2.690	0.012**
Computer Experience	0.517	3.426	0.002***	0.287	1.931	0.064
Model Parameters						
Total Observations	36			33		
R^2	0.691			0.618		
Adjusted R^2	0.627			0.530		
F-value (sig.)	10.794 (0.000)***			7.023(0.000)***		

R^2 Change	0.187	0.345
F-Change (sig.)	8.788 (0.001)***	11.749 (0.000)***
Durbin- Watson Stats	2.342	1.381

Model A shows the overall affective states mathematics performance of first session and Model B shows the overall affective states and mathematics performance for the second session. R^2-change and F-Change indicate the effect of controlling for the effect of educational level and computer experience.

**** $p < 0.01$; ** $p < 0.05$*

In Model A, the control variable that provided a statistically significant influence was computer experience, while for Model B, it was education. It was seen that for the first session, the participants with more prior computer experience scored better in the mathematics exercises of the Math-Mind game. This shows that during the first session, participants with a high educational level who had little computer experience struggled to get most of the questions right, not because they did not know, but because they found it difficult using the computer efficiently. Each equation appeared in the game screen for about 15 seconds, so a participant struggling with using the mouse found it difficult selecting the correct answer within the time frame. During the second session, it is seen that computer experience had no significant relationship and instead the educational level had a huge impact on the mathematics performance. This shows that by the second session, the participants with little or no computer experience had learned how to effectively play the Math-Mind game on the computer and now could use their knowledge acquired from school to easily complete the questions in the tasks.

For the affective states, it was seen that during the first session, engagement had a significant positive influence on mathematics performance while frustration had a significant negative influence. The findings are in line with the view that positive affective states enhance learning, while negative affective states have the adverse effect (Meyer & Turner, 2006; Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009). During the second session, engagement showed a consistent statistically significant positive influence on mathematics performance, while frustration showed no statistically significant influence. This could be explained by the proposition that participants with less computer experience during the first session experienced high levels of frustration when they struggled with the computer, thus accounting for their poor performance. Lastly, meditation and long-term excitement showed no statistically significant effect on mathematics performance for both sessions. The next section examined the impact of cognitive functions on mathematics performance.

5.9.2. Cognitive Functions and Mathematics Performance

Cognitive functions have been labelled as the building blocks of mathematics education (Blair & Razza, 2007; Bull and Scerif, 2001; Espy *et al.,* 2004). This section examines how each of the cognitive functions affected mathematics performance after controlling for the effect of educational level and computer experience. The first cognitive function examined was working memory.

5.9.2.1. Impact of Working Memory on Mathematics Performance

Working memory has shown a consistent statistically significant relationship to mathematics performance across many studies (Alloway & Alloway, 2010; Homes *et al.*, 2008; Kroesbergen *et al.,* 2011; Toll *et al.,* 2011). This relationship was examined in this dissertation and the findings are presented in Table 5.32 below.

The F-values for both models were significant, depicting that the overall models were significant. The control variables had no significant influence in Model A (F-Change = 0.761 and p>0.05) and contributed to only 2.4% of the overall variance. Similarly, in Model B the control variables showed no statistically significant influence (F-Change = 2.151 and p>0.05) and accounted for only 5.6% of the total variance (R^2-Change).

It was seen that for both models, working memory showed a statistically significant positive influence on mathematics performance. These findings are congruent with prior studies (Alloway & Alloway, 2010; Homes *et al.*, 2008; Kroesbergen *et al.*, 2011; Toll *et al.*, 2011) that have also established a positive relationship between working memory and mathematics performance. It should, however, be noted that working memory is a broad concept and the key working memory components captured for this study were a combination of the central executive working memory and storage working memory.

These findings supported the fact that the central executive working memory plays a central important role in the development of mathematic aptitude (Geary *et al.*, 2008; Grube & Barth, 2004). It can, therefore, be advocated that activities that enhance working memory should be adopted in South African schools as a means of addressing the math crisis.

Table 5.32: Relationship between Working Memory and Mathematics Performance

	Models					
Variables	**Model A**			**Model B**		
	Beta	T-Stats	(P-Value)	Beta	T-Stats	*P-Value*
Constant		-0.082	0.935		-1.930	0.063
Working Memory	0.572	3.198	0.003***	0.646	4.977	0.000***
Education	-0.078	-0.486	0.631	0.257	1.825	0.078
Computer Experience	1.692	1.232	0.227	0.006	0.039	0.969
Model Parameters						

Total Observations	36	33
R^2	0.482	0.624
Adjusted R^2	0.444	0.585
F-value (sig.)	10.321 (0.000)***	16.045 (0.000)***
R^2 Change	0.024	0.056
F-Change (sig.)	0.761 (0.476)	2.151 (0.135)
Durbin- Watson Stats	2.685	1.719

Model A shows the overall working memory and mathematics performance of first session and Model B shows the overall working memory and mathematics performance for the second session. R^2-change and F-Change indicate the effect of controlling for educational level and computer experience.

*** $p < 0.01$; ** $p < 0.05$

The next cognitive function examined was inhibitory control.

5.9.2.2. Impact of Inhibitory Control on Mathematics Performance

Researchers (Clark, *et al.,* 2010; Gilmore *et al.,* 2013; Lubin *et al.,* 2013) have explicated that inhibitory control plays a vital role in enhancing the learning of mathematics. In other to examine this relationship, a linear regression analysis was performed and the findings are presented in Table 5.33 below

Table 5.33: Relationship between Inhibitory Control and Mathematics Performance

Variables	**Models**					
	Model A			**Model B**		
	Beta	T-Stats	P-Value	Beta	T-Stats	*P-Value*
Constant		7.137	0.000***		9.777	0.000***
Inhibitory Control	0.044	0.224	0.824	0.517	3.665	0.002***
Education	0.056	0.315	0.755	0.259	1.284	0.209
Computer Experience	0.510	2.252	0.031**	0.165	0.922	0.364

Model Parameters		
Total Observations	36	33
R^2	0.330	0.364
Adjusted R^2	0.268	0.298
F-value (sig.)	5.264 (0.005)***	5.526(0.004)***
R^2 Change	0.169	0.096
F-Change (sig.)	4.032 (0.027)**	2.188 (0.130)
Durbin- Watson Stats	2.636	1.685

Model A shows the overall inhibitory control and mathematics performance of first session and Model B shows the overall inhibitory control and mathematics performance for the second session. R^2-change and F-Change indicate the effect of controlling for educational level and computer experience.

*** $p < 0.01$; ** $p < 0.05$

The F-values for both models were significant, depicting that the overall models were significant. The control variables had a significant influence in Model A (F-Change = 4.032, and p<0.05) and contributed 16.9% of the overall variance. However, in Model B the control variables showed no statistically significant influence (F-Change = 2.188, and p> 0.05). In model A computer experience was the only factor that showed a significant relationship to performance. It can be argued that during the first session, the participants were still trying to learn the BCI-based stop-signal task, which possibly explains why inhibitory control had no significant influence on mathematics performance.

Nonetheless, in model B, inhibitory control showed a statistically significant influence on mathematics performance. By the second session, the participants had trained their inhibitory control with the BCI-based stop signal task and now knew how to easily control the stop and go signals with cognitive actions. The positive significant influence of inhibitory control on mathematics performance observed in the second session (Model B) is congruent with prior studies (Gilmore *et al.*, 2013; Lubin *et al.*, 2013; Ponitz *et al.*, 2019; Walker & Henderson, 2012) that have shown that inhibitory control positively affects mathematics performance. This finding suggests that a BCI-based stop signal task could be an effective way of enhancing inhibitory control as a means of improving mathematics performance. The next cognitive function examined was math anxiety.

5.9.2.3. Impact of Math Anxiety on Mathematics Performance

Math anxiety has been known to have a negative effect on mathematics performance (Ashcraft and Krause, 2007; Jansen, *et al.*, 2013; Zakaria *et al.*, 2012). In order to examine the relationship in this study, a linear regression was performed and the results are presented in Table 5.34 below. In Model A, it is seen that math anxiety had a significant negative relationship to mathematics performance.

Table 5.34: Relationship Math Anxiety and Mathematics Performance

	Models					
Variables	**Model A**			**Model B**		
	Beta	T-Stats	(P-Value)	Beta	T-Stats	(*P-Value*)
Constant		8.632	0.000***		10.674	0.000***
Math Anxiety	-0.414	-3.204	0.003***	-0.353	-2.456	0.020**
Education	0.862	0.022	0.142	0.393	2.315	0.028**
Computer Experience	0.471	3.003	0.005***	0.153	0.899	0.376
Model Parameters						
Total Observations	36			33		
R^2	0.492			0.424		
Adjusted R^2	0.445			0.364		
F-value (sig.)	10.340 (0.000)***			7.104 (0.001)***		

R^2-Change	0.224	0.239
F-Change (sig.)	7.062 (0.003)***	6.000 (0.007)***
Durbin- Watson Stats	2.314	1.714

Model A shows the overall math anxiety and mathematics performance of first session and Model B shows the overall math anxiety and mathematics performance for the second session. R^2-change and F-Change indicate the effect of controlling for educational level and computer experience.

*** $p < 0.01$; ** $p < 0.05$

This indicates that high maths anxiety results in poor mathematics performance. The findings are consistent with prior studies (Ashcraft & Krause, 2007; Jansen *et al.*, 2013; Ramirez *et al.*, 2013; Zakaria *et al.*, 2012) which also indicated a significant negative relationship between math anxiety and mathematics performance. The significance of the F-Change value indicates that the control variables had a significant influence on the model and accounted for 22.4% of the total variance. It is seen that only computer experience had a significant positive effect on mathematics performance, showing that participants with more prior computer experience performed better. The significant amount of variance indicated that some of the anxiety could have been induced by the computer for participants with little or no computer experience.

In model B, math anxiety also had a statistically significant negative relationship to mathematics performance. It was, however, noted that in the second session (Model B), it was the level of education that accounted for significant differences in performance as opposed to computer experience as was the case in the first session (Model A). This indicates that by the second session, participants with little computer experience had already learned how to use the computer well in completing the exercises of the Math-Mind game. As such, there is little or no computer induced anxiety that could significantly affect the relationship between math anxiety and mathematic performance. This supports evidence form prior studies (Dupin-Bryant, 2002; Lee & Huang, 2014; Terujeni, Lavasani, Karamdust, 2013; Sam, Othman & Nordin., 2005) which indicated that exposure to computers reduces computer anxiety. The next cognitive function examined was number sense.

5.9.2.4. Impact of Number Sense on Mathematics Performance

Research over the years has shown a significant correlation between number sense and mathematics education (Mazzocco *et al.*, 2011; Wilson *et al.* 2009). This relationship was examined in this study by using a regression analysis and the results are presented in Table 5.35 below.

Table 5.35: Relationship between Number Sense and Mathematics Performance

	Models					
Variables	**Model A**			**Model B**		
	Beta	T-Stats	(P-Value)	Beta	T-Stats	(*P-Value*)
Constant		7.201	0.000***		2.849	0.011**
Number Sense	0.761	8.862	0.000***	0.743	4.325	0.000**
Education	-0.028	-0.25	0.777	0.059	0.314	0.757
Computer Experience	0.275	2.729	0.011**	0.001	0.002	0.998
Model Parameters						
Total Observations	36			33		
R^2	0.806			0.599		
Adjusted R^2	0.788			0.535		
F-value (sig.)	44.274 (0.000)***			9.442 (0.000)***		
R^2 Change	0.056			0.003		

F-Change (sig.)	4.653 (0.017)**	0.064(0.938)
Durbin- Watson Stats	1.642	1.346

Model A shows the overall number sense and mathematics performance of first session and Model B shows the overall number sense and mathematics performance for the second session. R^2-change and F-Change indicate the effect of controlling for educational level and computer experience.

*** $p < 0.01$; ** $p < 0.05$

The F-values for both models were significant, depicting that the overall models were significant. The control variables had a significant influence in Model A (F-Change = 4.653, and $p<0.05$) and accounted for 5.6% of the overall variance. However, in Model B the control variables showed no statistically significant influence and accounted for only 0.3% of the total variance. The results showed a consistent statistically significant positive influence of number sense on mathematics performance. These findings align with evidence from prior studies (Jordan *et al.*, 2008; Maryam *et al.*, 2011; Mazzocco *et al.*, 2011; Wilson *et al.* 2009).

Number sense is an important aspect of learning mathematics (Dunphy, 2007; Jordan *et al.*, 2010; Yang & Li, 2013) and the number sense skill can be trained from early childhood. It is, therefore, important to include number sense development from pre-school onwards as a long term strategy for addressing the math crisis.

A summary of the findings on how affective and cognitive states affect mathematics performance is presented in subsection 5.9.3 below

5.9.3. Summary on Mathematics Performance

When examining the effect of affective states on mathematics performance, it was observed that engagement had a statistically significant positive effect on mathematics performance, while frustration showed a statistically significant negative influence. With regards to the cognitive functions, all four (working memory, inhibitory control, math anxiety, and number sense) showed statistically significant influences on mathematics performance. The influence of working memory, inhibitory control and number sense were positive, while that for math anxiety was negative.

5.10. Post-session Usability Analysis

The post-test questions (Appendix E) were issued after the second session to evaluate the usability of the BCI-based Math-Mind game and the findings are described in this section. The first usability factor examined was the game engagement/experience questionnaire.

5.10.1. Game Engagement/Experience

The game engagement questionnaire measures a game player's engagement and user experience based on four major constructs, namely: physiological absorption, flow, presence, and immersion. The game engagement feedback from the participants was captured in the post-session questionnaire and the findings are presented in Table 5.36 below.

Table 5.36: Game Engagement/Experience

Items	Mean	Std. Dev	Skewness
Psychological absorption			
I feel different	3.32	1.82	-0.47
I feel scared when I do not know what to do	2.48	1.81	0.49
I lose track of where I am	2.80	1.80	0.14
Overall Psychological absorption score	**2.87**	**1.36**	**-0.09**
Flow			
The game feels real	4.84	1.81	-3.29
If someone talks to me, I do not hear them	2.36	1.87	0.76
Time seems to kind of standstill or stop	2.52	1.74	0.46
I did not feel tired	4.44	1.33	-2.31
I play without thinking about how to play	2.28	1.82	0.82
Playing makes me feel calm	4.64	0.34	-1.62

I feel like I just can't stop playing	4.68	0.85	-2.81
Overall Flow Score	**3.68**	**0.50**	**-0.08**
Presence			
Things seem to happen automatically	2.60	1.76	0.47
My thoughts go fast	3.52	1.61	-0.56
Overall Presence Score	**3.06**	**1.13**	**0.19**
Immersion			
I really get into the game	4.48	0.37	-1.98
Overall Immersion Score	**4.48**	**0.37**	**-1.98**

The results in Table 5.36 showed that the highest rating factor for game engagement/experience was *immersion* with a mean score of 4.48. The negative coefficient of skewness for immersion (-1.98) depicted that most of the participants rated immersion above the mean value. This indicates that the participants were fully engaged in the game playing experience as explicated by Banos *et al.* (2014) and Brockmyer *et al.* (2009). The second highest rated factor was *flow*, with a mean score of 3.68, followed by *presence* (mean score of 3.06), and lastly *psychological absorption* (mean score of 2.87).

Psychological absorption had the lowest value indicating that the participants did not have a complete altered state of consciousness (Brockmyer *et al.*, 2009). Brockmyer *et al.* (2009) explain that in the altered state of consciousness, the affective states are less accessible to consciousness and thoughts are separated from feelings. Also, the high score for the game flow indicates that most participants did not experience high negative emotions like frustration and anxiety as these negative emotions are antithetical to the flow state. The next usability factor analysed was the overall user reaction to the system based on the QUIS.

5.10.2. Satisfaction Analysis Based on the QUIS

The overall reaction of the participants about the BCI-based Math-Mind game was captured with the QUIS and the results are presented in Table 5.37 below.

Looking at the overall reaction, participants mostly expressed positive emotions about the system. The highest rated factor for the overall reaction was that the system was *satisfying* (8.28). The lowest rated factor was *stimulating* with a value of 7.72, still showing that most participants considered the game to be stimulating. Furthermore, all the factors under the overall reaction to the software have a negative coefficient of skewness, indicating that most participant ratings were to the right of the mean. This implies that most of the ratings favoured the positive emotions (wonderful, easy, satisfying, stimulating and flexible).

Table 5.37: Overall Participant Reaction to the System

Overall Reaction to Software					
		Mean	Std. Dev	Skewness	
	Terrible	7.60	2.22	-1.29	Wonderful
	difficult	8.00	1.26	-0.96	easy
	Frustrating	8.28	1.67	-3.10	satisfying
	Dull	7.72	1097	-1.43	stimulating
	Rigid	7.80	2.00	-1.39	flexible
Screen					
Reading characters on screen	Hard	8.40	1.94	-3.24	easy
Organization of information	Confusing	8.72	1.06	-4.16	Very clear
System Capabilities					
System speed	Too slow	7.60	1.61	-0.59	Fast enough
System tends to be	Noisy	8.92	0.28	-3.29	Quiet
Correcting your mistakes	difficult	7.28	2.95	-1.51	easy

With regards to the screen factors, the participants indicated that it was easy reading characters on the screen (mean = 8.40) and that the information was organized in a clear manner (mean = 8.72). With respect to the system capabilities, the participants indicated that the system was fast enough, quiet, and easy to correct mistakes. The next usability aspect examined was usefulness, satisfaction, and ease of use based on the USE questionnaire.

5.10.3. Usefulness, Satisfaction, and Ease of Use Questionnaire

Participants provided ratings for the system on the USE questionnaire and the findings are presented in Table 5.38 and Figure 5.15 below.

From Table 5.38, it is evident that all the participants provided the maximum rating of five indicating that they were satisfied with the application. The participants also indicated that the application was useful and easy to use.

Table 5.38: USE questionnaire ratings

Statement	Mean	Std Dev.	Skewness
The BCI device was easy to use	3.80	1.44	-0.62
The game was easy to play	4.76	0.44	-1.30
This application can be useful in helping me to learn mathematics	4.88	0.33	-2.49
I can play the game without written instructions	3.84	1.75	-1.01
It is easy to learn how to play the game	4.80	0.41	-1.34
I am satisfied with the application	5.00	0.00	-
I would recommend it to a friend.	4.36	1.32	-2.16
It is fun to use	4.36	1.32	0.46
It is pleasant to use	4.44	1.33	-2.31

Using the results in Table 5.38, the overall average ratings for usefulness, satisfaction and ease of use were computed and the finding presented in Figure 5.16 below.

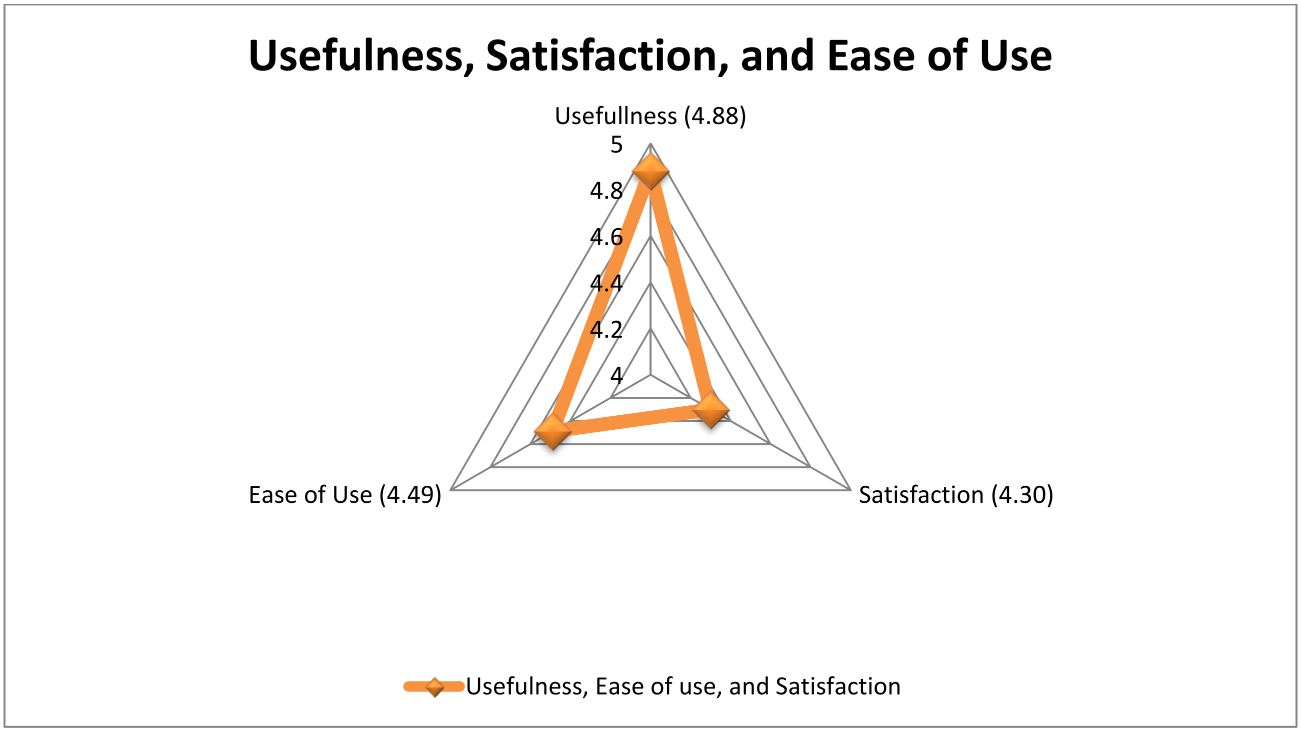


Figure 5.16: Usefulness, Satisfaction, and Ease of Use

The results in Figure 5.16 showed that usefulness (mean = 4.88) was the highest rated factor, followed by ease of use (mean = 4.49). Although satisfaction was the least rated among the three factors, it still had a meaningful high mean rating depicting that participants were satisfied with the system. The next usability aspect examined was the technology usage behaviours based on the Survey of Technology Use Questionnaire (SUTU).

5.10.4. Survey of Technology Use (SOTU)

The SOTU was used to examine the profile of the participants. The findings are presented in Figure 5.17 below. The results indicated that most of the participants preferred to work in groups, control their own learning space, and were curious and excited about new things. This indicated participants' willingness to easily adopt new approaches to learning, such as the BCI-based approach for developing cognitive functions.

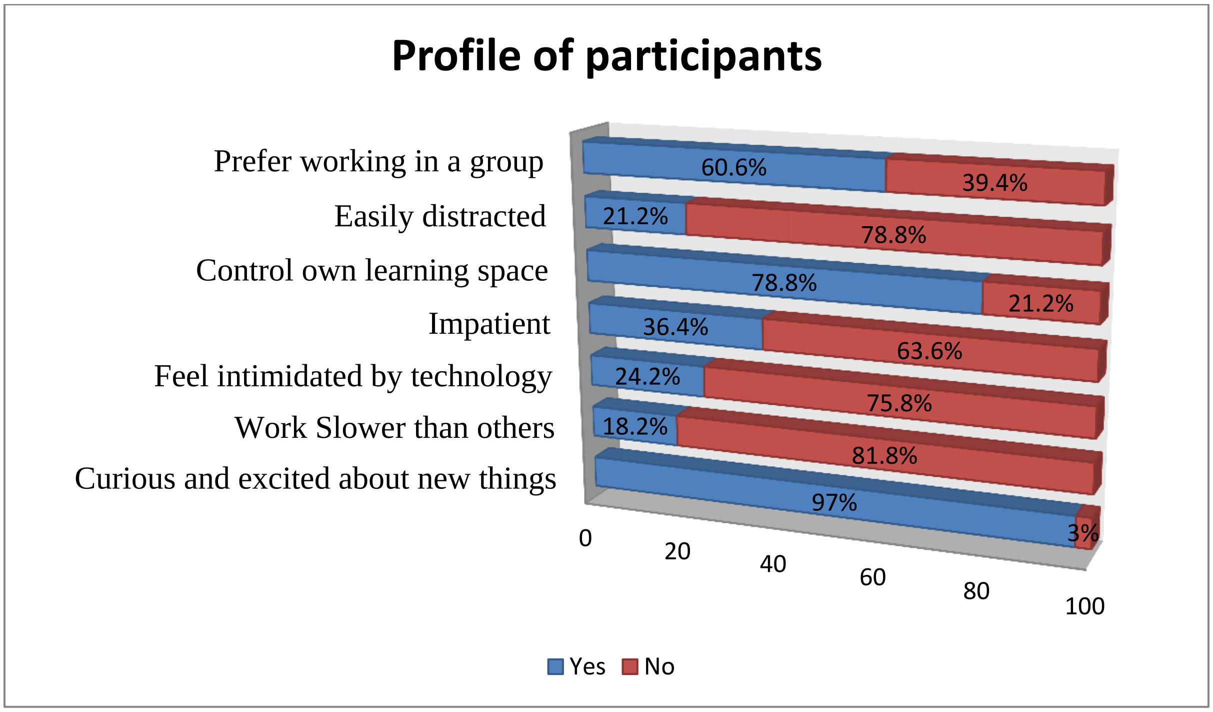


Figure 5.17: Profile of Participants based on SOTU

The fact that many children preferred working in groups indicated why recent studies (Eseryel, Law, Ifenthaler, Xun & Miller, 2014; Hou, 2013; Voulgari, Komis & Sampson, 2014; Wu, Richards & Saw, 2014) have continuously advocated for multiplayer game platforms as a means of fostering game-based learning. These studies explicate that multiplayer games enhance student motivation, engagement levels and problem solving skills.

However, in the context of BCI games, the development of multiplayer games is still in its infancy with some key challenges. One such challenge is that the BCI game players focus a lot of attention on using the BCI device to control the game, which reduces their level of attention to collaborate with the co-payers (Gürkök, Nijholt, Poel & Obbink, 2013). It was also observed was that most of the participants did not feel intimidated by new technology, were patient, and not easily distracted. The next usability factor examined was the overall system usability for the game and the Emotiv EPOC BCI.

5.10.5. Overall Usability SUS

The SUS has been used for many years as a measure of a system's overall usability. In this section the SUS (Appendix E) was used to capture the overall usability of the Math-Mind game and the Emotiv EPOC BCI device and the results are presented in Figure 5.18 below.

The findings showed that the mean SUS score for the Math-Mind game was higher than for the Emotiv EPOC BCI. This indicates that the participants experienced better overall usability of the Math-Mind game as opposed to the Emotiv BCI. However, SUS scores above 70 are considered good and acceptable scores (Bangor, Kortum & Miller, 2009). As such, the Emotiv EPOC BCI still showed a good overall usability. One factor that contributed to the poor usability as indicated by most participants was the wet sensors which made some participants uncomfortable.

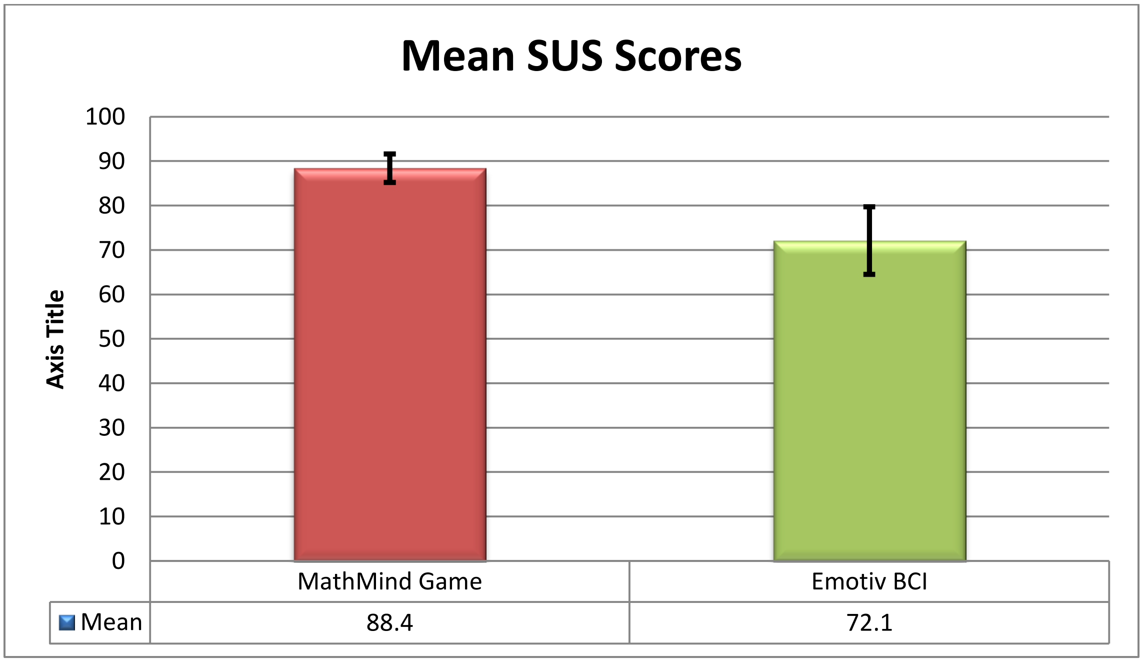


Figure 5.18: SUS Scores

Nonetheless, this problem has been addresses with the new version of the Emotiv BCI (Figure 5.19 below) and will possible increase its usability and adoption by the younger generation.

Figure 5.19: Emotiv Insight

5.10.6. Subjective Usability Measures and Brain Activity

Brain activity has been known to influence human emotions (Hosseini, Talepassand & Bigdeli, 2009; Matsumoto, Ichikawa, Kanayama, Ohira & Iidaka, 2006). Because emotions determine how a user feels about something, it is possible that brain activity can influence usability /user experience.

To examine this relationship, a Pearson correlation was performed and the findings are presented in Table 5.39 below. The findings indicated that only the Gamma brain activity had a significant relationship with the subjective usability/user experience measures. The Gamma brain activity showed a significant negative relationship with flow, immersion, usefulness, and the overall usability of the Math-Mind Game. The negative relationship was expected since high Gamma brain activity is associated with negative emotions (Hosseini *et al.,* 2009; Oathes *et al.,* 2008). This, therefore, indicated that participants' higher Gamma brain activity gave poor usability ratings due to the negative emotions they experienced while using the system. The next section examines how usability and user experience measures are related to cognitive functions and affective states.

5.10.7. Subjective Usability Measures Cognitive Functions

The results in Table 5.40 depict findings of the analysis that examined the correlation between subjective usability / user experience measures and cognitive functions and affective states. For cognitive functions, working memory showed a significant negative relationship with usefulness and a significant positive relationship with the overall usability of the Emotiv EPOC BCI device. Inhibitory control showed a positive statistically significant relationship with absorption and the overall usability of the Emotiv EPOC BCI device.

Math anxiety showed a positive statistically significant relationship with immersion and usefulness, and a negative statistically significant relationship with flow and the overall usability of the Emotiv EPOC BCI. Number sense showed a positive statistically significant relationship to flow and a negative statistically significant relationship with usefulness and the overall usability of the Math-Mind game.

The findings indicated that participants with low levels of working memory and number sense, rated the application as highly useful probably because of the possibilities that it showed in terms of enhancing working memory and number sense skills. Similarly, participants with high levels of math anxiety rated the application as very useful because of its potential in reducing math anxiety levels. Furthermore, having a high level of the flow state indicated that the participants

Table 5.39: Correlation Matrix between Usability/User Experience Measures and Brain Activity

Subjective usability /User Experience Measures	Left Hemisphere Brain Activity					Right Hemisphere Brain Activity				
	Delta	**Theta**	**Alpha**	**Beta**	**Gamma**	**Delta**	**Theta**	**Alpha**	**Beta**	**Gamma**
Absorption	-0.055	-0.116	-0.136	-0.118	-0.083	-0.031	0.007	-0.003	0.165	0.149
Flow	0.033	0.068	0.113	0.052	0.021	0.011	-0.018	-0.015	0.140	-0.345**
Presence	0.056	-0.019	-0.043	-0.074	0.020	0.079	0.029	0.017	0.044	0.276
Immersion	0.182	0.188	0.200	0.196	0.170	0.141	0.126	0.115	0.147	-0.623***
Usefulness	0.167	0.164	0.166	0.185	0.163	0.141	0.125	0.116	0.1465	-0.552***
Ease of Use	0.123	0.113	0.132	0.140	0.107	0.056	0.006	-0.002	-0.051	0.061
Satisfaction	0.073	0.104	0.127	0.065	0.067	0.072	0.019	-0.001	0.067	-0.011
SUS Game	0.047	0.148	0.178	0.144	0.097	0.024	0.059	0.071	0.006	-0.324**
SUS BCI	-0.324	-0.262	-0.231	-0.304	-0.299	-0.305	-0.296	-0.301	-0.150	-0.005

*** p< 0.01; **p<0.05

Table 5.40: Correlation Matrix between Usability/User Experience Measures and Cognitive Functions and Affective States

Subjective usability /User Experience Measures	Cognitive Functions				Affective States			
	Working Memory	**Inhibitory Control**	**Math Anxiety**	**Number Sense**	**Engagement**	**Meditation**	**Frustration**	**Long-term Excitemen t**
Absorption	0.149	0.470***	0.018	0.027	0.029	-0.169	-0.070	0.143
Flow	-0.257	-0.248	-0.338**	0.348**	-0.126	-0.213	-0.203	0.210
Presence	0.199	0.188	0.254	-0.028	0.202	-0.103	-0.104	0.385**
Immersion	-0.311**	-0.259	0.448***	-0.282	-0.017	0.144	0.243	0.351**
Usefulness	-0.446***	-0.277	0.492***	-0.416**	-0.219	0.038	-0.310**	0.306*
Ease of Use	0.023	-0.088	0.139	-0.289	0.063	-0.435**	-0.053	0.133
Satisfaction	0.052	-0.038	0.081	0.050	-0.007	0.031	0.130	0.131
SUS Game	-0.052	-0.150	0.090	-0.437***	0.368**	0.087	0.174	-0.039
SUS BCI	0.406**	0.360**	-0.414**	0.165	0.370**	0.108	-0.321**	-0.204

*** p< 0.01; **p<0.05

were in control of the game and the game-based learning space (Brockmyer *et al.*, 2009). This explained why participants with a high level of math anxiety rated low in the flow state, while those with high number sense rated high in the flow state.

For the Affective states, it was observed that engagement had a positive statistically significant relationship with the overall usability of the Math-Mind game and the Emotiv EPOC BCI. Meditation showed a negative statistically significant relationship with ease of use. Frustration showed a negative statistically significant relationship with usefulness and overall usability of the Emotiv EPOC BCI. This indicated that participants who experienced frustration while using the Emotiv EPOC (especially the wet sensors) gave it an overall poor usability rating. Long-term excitement showed a positive statistically significant correlation with presence and immersion.

5.11. Chapter Summary

In this chapter, the analysis of the captured data and the findings obtained were reported. The findings reported were grounded in the context of existing evidence as a means to clearly determine the contributions of this study, as well as to sufficiently address the research problem under investigation. The next chapter will provide discussions and conclusions by clearly articulating how the study addressed the research questions and achieved the research objectiv

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

The previous chapter provided a detailed explanation and discussion of the empirical findings of this study. In this chapter, conclusions and recommendations are established based on the findings in chapter 5. Figure 6.1 provides a schematic representation of the chapter outline. In order to put this study into context, the next section provides an overview.

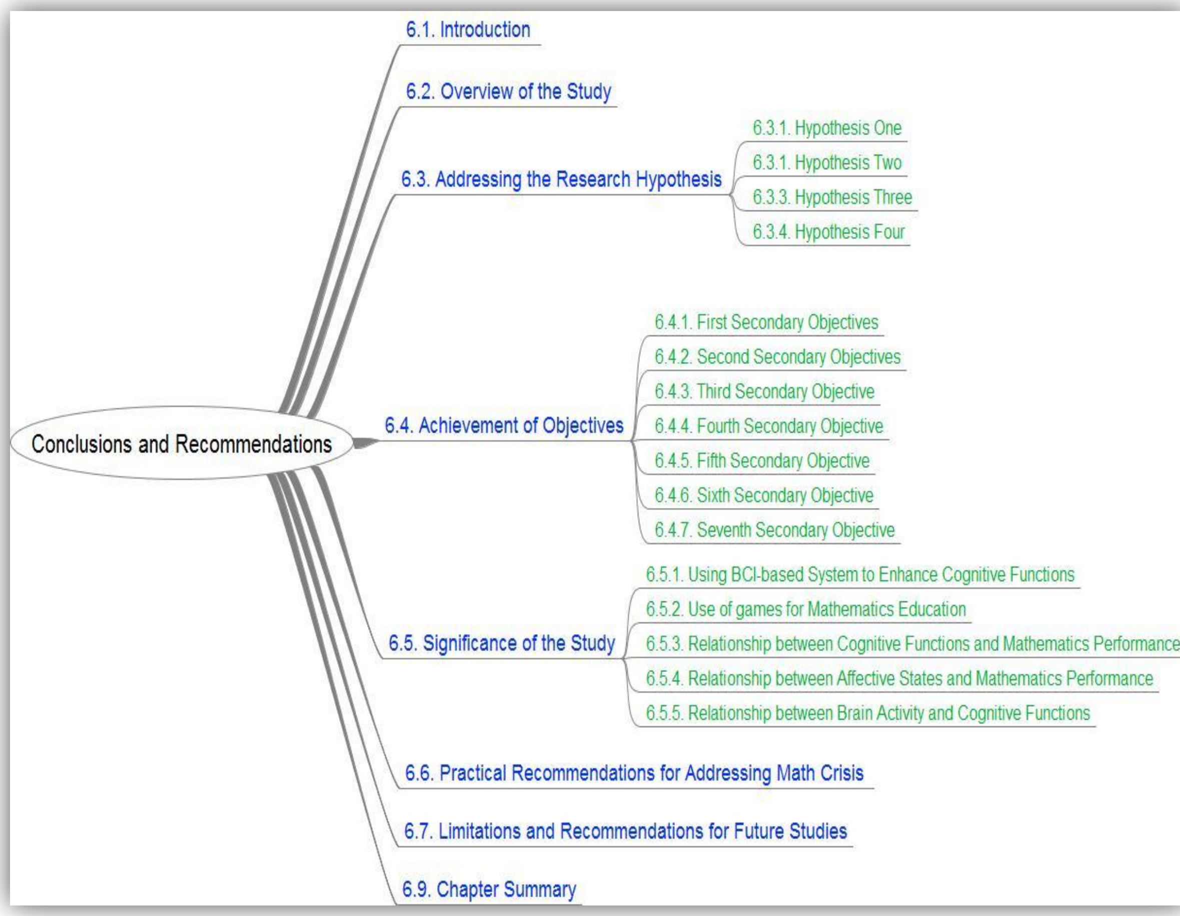


Figure 6.1: Mind-map of Chapter Six

6.2. Overview of the Study

The first chapter provided background as a means of establishing the context in which the study was undertaken. A brief review of existing studies was done to explain the context of this study and to clearly establish the research problem. After establishing the research problem, the chapter outlined the research questions, research objectives, hypothesis, research methodology, research limitations, and an outline of the dissertation. Chapter two provided an overview and history of BCI technologies; the functioning of a BCI system from signal acquisition to controlling an application; the different brain signals used for BCI operations; and several uses of a BCI system. In Chapter three, a detailed review of the relationship between mathematics educational games and mathematics attainment was provided. Also, the chapter elaborated on how the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) impacted on mathematics attainment. Lastly, the chapter explicated how the incorporation of cognitive skills in games could be useful for developing mathematics skills. In Chapter four, the detailed research design and methodology was explained. Chapter five then focused on the analysis of the research data and discussion of the findings thereof.

This study was chosen as a means of addressing the current problem of a high "math crisis" in South Africa. Even though South Africa faces a huge problem in terms of shortage in mathematics competencies, solutions to address the problem have largely overlooked affective and cognitive components of learning (Graven, *et al.*, 2013; Hlalele, 2012; Kloppers & Grosser, 2010; Mutodi & Ngirande, 2014; Taylor, 2008). This is irrespective of the fact that there is significant evidence from the developed world indicating that affective and cognitive aspects of learning play a vital role in the development of mathematics skills (Abolmaali & Memari, 2013; Alloway & Passolunghi, 2011; Gilmore *et al.*, 2013; Jansen *et al.*, 2013; Jordan *et al.*, 2010;

Oberle & Reichl, 2013; Swanson & Kim, 2007; Witt, 2011; Zakaria *et al.,* 2012). While cognitive functions have been known to account for significant differences in mathematics attainment among children, there is unexpectedly little research examining the possibility of increasing young children's cognitive functions (Witt, 2011). As such, this study adopted the BCI-based system as a tool for enhancing cognitive functions as a means to address the math crisis problem. The BCI solution was chosen based on expert opinions which clearly indicated that BCI devices have a huge potential for educational purposes as they can be used for enhancing cognitive and affective (i.e. cognitive psychological factors) components of learning (Plass-Oude Bos *et al.,* 2010; Van Erp, Lotte & Tangermann, 2012).

To achieve the desired goal this study combined existing neuroscience, psychological and mathematical education paradigms on cognitive functions with recent BCI paradigms to develop a BCI-based solution for neuroscience, psychological and mathematical education. In this light, the primary objective examined in the study was to explore the impact of a BCI mathematics game as a tool for facilitating the development of cognitive functions that enhance mathematics skills in children. To achieve this objective, a well-structured within-subject longitudinal research design was adopted and carried out to test the impact of the developed BCI-based system on enhancing cognitive functions. Details on how the hypothesis and objectives were achieved in this study are discussed in section 6.3 and 6.4 respectively. Furthermore, the significance of the study in respect to addressing the research problem is explicated in section 6.5 below.

6.3. Addressing the Research Hypotheses

In chapter one (section 1.6) five hypotheses' were developed in line with the established research questions. In this section, each of the hypotheses is discussed and conclusions from the findings are made based on the hypotheses.

6.3.1. Hypothesis One

The null hypothesis ($H_{1,0}$) was stated as *"short term playing of a BCI educational game does not enhance selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense)."*

This hypothesis can be further divided into four sub-hypotheses (1a, 1b, 1c, and 1d) with each sub-hypothesis depicting the findings of a specific cognitive function. These sub-hypotheses and the outcomes are presented in Table 6.1 below:

Table 6.1: Outcome of Hypothesis One Based on the Sub-hypothesis

Null Hypothesis	Analysis to address the hypothesis	Outcome
$\boldsymbol{H_{1a,0}}$ **:** Short term playing of a BCI educational game does not enhance working memory.	Section 5.6.1	Reject
$\boldsymbol{H_{1b,0}}$ **:** Short term playing of a BCI educational game does not enhance inhibitory control.	Section 5.6.2	Reject
$\boldsymbol{H_{1c,0}}$ **:** Short term playing of a BCI educational game does not enhance math anxiety.	Section 5.6.3	Reject
$\boldsymbol{H_{1d,0}}$ **:** Short term playing of a BCI educational game does not enhance number sense.	Section 5.6.4	Reject

Significant results were found for each of the four sub-hypothesis and as such all the respective null hypotheses were rejected. Consequently, the entire null hypothesis ($H_{1,0}$) was rejected. It can thus be concluded that *"short term playing of a BCI educational game can significantly enhance* *selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense).*" Hypothesis two will be examined next.

6.3.2. Hypothesis Two

For hypothesis two, the null hypothesis ($H_{2,0}$) was stated as "*there is no relationship between brain activity (Alpha, Beta, Theta, Alpha, Delta, and Gamma) and cognitive functions (working memory, inhibitory control, math anxiety, and number sense*)." This hypothesis was analysed in section 5.7.4 using a Pearson correlation analysis. The analysis was detailed as it examined brain activity over EM (level one - easy mathematics exercises) and DM (level five - difficult mathematics exercises) tasks across the left and right brain hemispheres. The significant relationships for each of the cognitive functions are detailed in Table 6.2 below.

Table 6.2: Significant Relationships between Brain Activities and Cognitive Functions

Cognitive Functions	**Brain activity with significant relationship**				
	Alpha	Beta	Theta	Delta	Gamma
Working memory		**X**		**X**	**X**
Inhibitory control				**X**	**X**
Math anxiety					**X**
Number sense	**X**				

In Table 6.2 "X" indicates statistically significant relationships. Except for the Theta brain activity, it was seen that each of the other four brain activities (Alpha, Beta, Delta, and Gamma) showed a statistically significant relationship with at least one of the selected cognitive functions. Based on these findings, the following conclusions were made regarding hypothesis two:

- There is a statistically significant relationship between Alpha brain activity and number sense.
- There is a statistically significant relationship between Beta brain activity and number sense.
- There is no significant relationship between Theta brain activity and any of the selected cognitive functions.
- There is a statistically significant relationship between Delta brain activity and two cognitive functions (working memory and inhibitory control).
- There is a statistically significant relationship between Gamma brain activity and three cognitive functions (working memory, inhibitory control, and math anxiety).

The next hypothesis examined was hypothesis three.

6.3.3. Hypothesis Three

For hypothesis three, the null hypothesis ($H_{3,0}$) was stated as *"the user's cognitive functions are not influenced by his/her affective state of mind."* Four affective states (engagement, meditation, frustration, and long-term excitement) were examined and the relationships with cognitive functions are presented in Table 6.3 below.

Table 6.3: Relationship between Cognitive Functions and Affective Mind States

Cognitive Functions	**Affective states with significant relationship**			
	Engagement	Meditation	Frustration	Long-term Excitement
Working memory	**X**			
Inhibitory control		**X**		**X**
Math anxiety			**X**	**X**
Number sense	**X**			

In Table 6.3 “X” indicates statistically significant relationships. The detailed results were presented in section 5.8.2. It became evident that each of the affective states influenced at least one of the cognitive functions. Based on these findings, the following conclusions were derived:

- Working memory is influenced by engagement.
- Inhibitory control is influenced by meditation and long-term excitement.
- Math anxiety is influenced by frustration and long-term excitement.
- Number sense is influenced by engagement.

Next, hypothesis four was examined.

6.3.4. Hypothesis Four

For hypothesis four, the null hypothesis ($H_{4,0}$) was stated as “*there is no relationship between the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) and mathematics attainment.*”

Table 6.4: Outcome of Hypothesis Four Based on the Sub-hypotheses

Null Hypothesis	**Analysis to address the hypothesis**	**Outcome**
$\boldsymbol{H_{4a,0}}$ **:** There is no relationship between working memory and mathematics attainment.	Section 5.9.2.1.	Reject
$\boldsymbol{H_{4b,0}}$ **:** There is no relationship between inhibitory control and mathematics attainment.	Section 5.9.2.2.	Reject
$\boldsymbol{H_{4c,0}}$ **:** There is no relationship between math anxiety and mathematics attainment.	Section 5.9.2.3.	Reject
$\boldsymbol{H_{4d,0}}$ **:** There is no relationship between number sense and mathematics attainment.	Section 5.9.2.4.	Reject

This hypothesis can be further divided into four sub-hypotheses (4a, 4b, 4c, and 4d) with each sub-hypothesis depicting the findings of a specific cognitive function. These sub-hypotheses and the outcomes are presented in Table 6.4 above.

Significant results were found for each of the four sub-hypotheses; consequently, all the respective null hypotheses were rejected. It can thus be concluded that *"there is a relationship between the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) and mathematics attainment.*" The conclusions derived on the achievement of the research objectives are discussed in the proceeding section.

6.4. Achievement of Objectives

In chapter one (Section 1.5) primary and secondary objectives were developed to guide the study in addressing the established research problem. In this section, the success of this study is examined based on the attainment of the specified research objectives. The primary objective of the study was to explore the impact of a BCI mathematics game as a tool for facilitating the development of cognitive functions that enhance mathematics skills in children. This objective was achieved through seven secondary objectives discussed below.

6.4.1. First Secondary Objectives

The first secondary objective was to review the literature of BCI interfaces with a particular interest in BCI's for gaming, usability and education. This was achieved in chapter two. A detailed literature review on the components of a BCI system, from signal acquisition to end user BCI applications, was provided (Section 2.4). Furthermore, the different types of brain activities used for controlling BCI systems were reviewed (section 2.5). Lastly, the uses of BCI devices in gaming, usability and education were explained (Section 2.6).

6.4.2. Second Secondary Objectives

The second secondary objective was to review the literature on using games for educational purposes with a particular interest in mathematics educational games. This objective was achieved in chapter three where a detailed literature review on the relationship between educational games and mathematics education was provided. It was observed that several studies (Bragg, 2012; Burguillo, 2010; Chun-Yi & Ming-Puu, 2009; Delacruz, 2011; Kebritchi *et al.*, 2010; Shin *et al.*, 2012) have found a positive relationship between mathematics educational games and mathematics performance, while others (Çankaya & Karamete, 2009; Kim & Chang, 2010; Lim *et al.*, 2006) have found mixed results.

6.4.3. Third Secondary Objective

The third secondary objective was to examine the objective measures of cognitive functions using a non-invasive BCI device (Emotiv EPOC). This objective was achieved in section 5.5. The objective measures of cognitive functions were compared to the subjective measures from widely validated neuropsychology questionnaires. It was observed that the subjective measures of central executive working memory and storage memory were significantly related to the BCI-based measures of working memory. Also, the subjective measures for inhibitory control, math anxiety, and number sense were all related to the objective measures.

6.4.4. Fourth Secondary Objective

The fourth secondary objective was to determine the impact of a BCI-based system on the training of the selected cognitive functions that enhance mathematics skills. Empirical analysis (Section 5.6.) was conducted as a means of attaining this objective. The findings showed that the

BCI-based system could be used to effectively train all four of the selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense).

6.4.5. Fifth Secondary Objective

The fifth secondary objective was to examine the influence of affective mind states on cognitive functions. This objective was achieved in section 5.8.2. It was observed that positive affective states (engagement and meditation) had a positive influence on working memory, inhibitory control and number sense. On the other hand, negative affective states (frustration and long-term excitement) showed a significant positive relationship with math anxiety and had a significant negative influence on inhibitory control.

6.4.6. Sixth Secondary Objective

The sixth secondary objective was to determine the relationship between brain activity (Alpha, Beta, Theta, Delta, and Gamma) and the selected cognitive functions. This objective was attained in section 5.7.4. Detailed analysis of the relationship was provided based on task difficulty and brain region (left and right hemispheres). All the types of brain activities, except for Theta, showed a statistically significant relationship with at least one of the cognitive functions.

6.4.7. Seventh Secondary Objective

The seventh secondary objective was to determine the impact of affective states and cognitive functions on mathematics performance. This objective was achieved in section 5.9. In section 5.9.1, it was observed that engagement had a significant positive impact on mathematics performance, while frustration had a significant negative impact. These findings confirmed existing evidence (Meyer & Turner, 2006; Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009) that positive affective states enhance educational performance, while negative affective states repress educational performance. In section 5.9.2 it was observed that all four selected cognitive functions had a significant impact on mathematics performance. This confirmed the findings from prior studies (Alloway & Alloway, 2010; Ashcraft and Krause, 2007; Clark, *et al.*, 2010; Gilmore *et al.*, 2013; Homes *et al.*, 2008; Jansen, *et al.*, 2013; Jordan *et al.*, 2008; Kroesbergen *et al.*, 2011; Lubin *et al.*, 2013; Maryam *et al.*, 2011; Mazzocco *et al.*, 2011; Toll *et al.*, 2011; Wilson *et al.* 2009; Zakaria *et al.*, 2012) supporting the impact of cognitive functions on mathematics performance.

6.5. Significance of the Study

South Africa currently faces a huge shortage of mathematics skills, a problem commonly referred to as the "math crisis". However, existing solutions to address the problem have overlooked the role of cognitive functions in improving mathematics aptitude. For example, Graven *et al.* (2013) has indicated the need to maintain a strong focus on number sense in South African schools. Similarly Kloppers and Grosser (2010) elucidated that South African learners lacked the cognitive skills necessary for enhancing mathematics aptitude. Researchers (Hlalele, 2012; Mutodi & Ngirande, 2014) in South Africa studying the prevalence of math anxiety in schools have documented that most learners experience math anxiety and subsequently called for the need to implement strategies that can address math anxiety and reduce its effect on mathematics performance. According to Taylor (2008) the low cognitive level among South African learners can be attributed to the ineffective teaching methods in most South African schools. Kloppers and Grosser (2010) support this view and call for the need to improve the training of educators and enhance their own cognitive skills so that they could be better placed in developing the cognitive skills of learners. Given that educators are not adequately equipped to develop the cognitive functions of learners, it becomes imperative to develop solutions that learners can adopt and use to enhance these functions.

Approaches like cognitive behavioural group therapy (CBGT) and Feuerstein Instrumental Enrichment programme (FIE) that are used in developed countries can be adopted for South African use. However, these solutions require trained professionals to administer them, thus making it difficult to use in the broader context of South Africa. In this light, Smith and Hardman (2014) have called for the need to study how computers and technologies can be used as effective tools for developing cognitive functions in South African schools. This study, thus, investigated the potential of a BCI-based system as a tool for enhancing the cognitive functions that are important in improving mathematics performance in learners. In order to clearly establish the significance of this study, some key findings and their importance in addressing the "math crisis" problem in South Africa are discussed below.

6.5.1. Using a BCI-based System to Enhance Cognitive Functions

As mentioned above, South African learners have been known to have low cognitive functions (Graven *et al.,* 2013; Hlalele, 2012; Kloppers & Grosser, 2010; Mutodi & Ngirande, 2014; Taylor, 2008). However, little has been done to improve the cognitive functions of learners in South Africa. Existing strategies that can be adopted for enhancing cognitive functions, such as CBGT and FIE, require trained professionals to administer. These professionals are hard to find in South Africa, thus making it difficult to implement such approaches on a broader scale.

This study brought about a novel approach for enhancing cognitive functions based on the capabilities of the BCI system. The findings (Section 5.6.) revealed that all four selected cognitive functions (working memory, inhibitory control, math anxiety, and number sense) could be enhanced with the BCI-based system. Undisputable evidence (Alloway & Alloway, 2010; Ashcraft & Krause, 2007; Clark, *et al.,* 2010; Gilmore *et al.,* 2013; Homes *et al.*, 2008; Jansen, *et al.,* 2013; Jordan *et al.,* 2008; Kroesbergen *et al.,* 2011; Lubin *et al.,* 2013; Maryam *et al.,* 2011; Mazzocco *et al.,* 2011; Toll *et al.,* 2011; Wilson *et al.* 2009; Zakaria *et al.,* 2012) from the developed world clearly indicated that these four cognitive functions have a statistically significant influence on mathematics performance. Consequwntly, the principles and techniques embedded in the proposed BCI-based system in this study add to the existing approaches available for enhancing cognitive functions. Moreover, the BCI-based system is easier and cheaper to administer than existing approaches (e.g. CGBT and FIE), and does not require professional supervision. Adopting such a tool in households or schools can significantly ameliorate the "math crisis" problem in South Africa as increases in cognitive skills will result in increased mathematics attainment.

Furthermore, in a broader context, BCI researchers (Bos *et al.,* 2010; van Erp *et al.,* 2012) have outlined the potential use of BCI devices for educational purposes, especially in enhancing cognitive functions. However, to date, little empirical evidence exists to support these views. This study acts as part of the empirical evidence indicating the possible usage of BCI technology for educational purposes.

6.5.2. Use of Games for Mathematics Education

The use of computer games for educational purposes has gained enormous interest from practitioner and academic domains over that past decade (Begg, *et al.,* 2005; Chuang and Chen, 2009; Gee, 2007; Kebritchi, *et al.,* 2008; Scanlon *et al.,* 2005). While several studies (Bragg, 2012; Burguillo, 2010; Chun-Yi & Ming-Puu, 2009; Delacruz, 2011; Kebritchi *et al.,* 2010;

Shin, *et al.,* 2012) have shown that computer games have a positive impact on mathematics education, others (Çankaya & Karamete, 2009; Godfrey & Stone, 2013; Kim & Chang, 2010; Lim *et al.*, 2006; Nusir *et al.,* 2012) have yielded mixed results or no results at all.

This study contributes to the debate by indicating that a BCI-based computer educational game can have a positive influence on mathematics education by enhancing the cognitive functions required for improving mathematics attainment. Moreover, the use of computer games for mathematics educational purposes has been understudied in South Africa. This study, thus, contributes to this domain and can act as a basis for other studies that intend to use computer games in addressing the math crisis problem in South Africa.

6.5.3. Relationship between Cognitive Functions and Mathematics Performance

Cognitive functions have been labelled as the building blocks of mathematics education (Blair & Razza, 2007; Bull & Scerif, 2001; Espy *et al.,* 2004). The poor level of mathematics skills among South African learners has been partly attributed to lack of cognitive functions (Graven *et al.*, 2013; Hlalele, 2012; Kloppers & Grosser, 2010; Mutodi & Ngirande, 2014; Taylor, 2008). However, unlike in the developed world, researchers in South Africa have not explicitly examined the relationship between cognitive functions and mathematics performance within South Africa. For example, Hlalele (2012) and Mutodi and Ngirande (2014) have studied the level of math anxiety in South African schools, but have not empirically examined how the different levels of math anxiety affect mathematics performance.

This study extends the assertions of the above researchers by empirically indicating that the level of math anxiety has a significant influence on mathematics performance in South Africa. Similarly, the relationship between other cognitive functions (e.g. working memory, number sense, and inhibitory control) and mathematics performance has also been understudied in South Africa. This study thus provides a basis from which larger educational and psychological studies in South Africa can emerge to provide country-wide evidence on how cognitive skills are related to mathematics performance in South Africa.

6.5.4. Relationship between Affective States and Mathematics Performance

It is known that positive affective states enhance learning, while negative affective states have an adverse effect on learning (Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009). However, in South Africa, studies have not examined how negative and positive affective states impact on mathematics performance of learners.

This study showed that, among South African learners, engagement (a positive affective) had a statistically significant positive influence on mathematics performance, while frustration (a negative affective state) showed the adverse effect. Mediation and long-term excitement did not show a statistically significant influence on mathematics. These findings provide practical implications for teachers and policy makers as they can now try to examine how selected affective states influence the mathematics performance of learners. This will help in developing strategies that promote positive affective states and positive attitudes towards mathematics.

6.5.5. Relationship between Brain Activity and Cognitive Functions

Brain activity has an influence on cognitive functions. Therefore, to enhance some cognitive functions, it is imperative to either supress or evoke certain brain activities. In section 5.7.4, it was observed that Gamma brain activity was positively associated with math anxiety and negatively associated with working memory and inhibitory control. These findings are congruent with existing studies (Albrecht *et al.*, 2013; Oathes *et al.*, 2008) which indicated that increases in

Gamma brain activity result in increased anxiety-like behaviour. Given that high levels of anxiety have negative impacts on mathematics performance, it becomes important to find ways of supressing Gamma brain activity as a means of controlling disruptive levels of math anxiety. Moreover, supressing Gamma activity will also result in increased working memory and inhibitory control.

The findings also showed that Alpha and Beta brain activity had a significant positive impact on cognitive functions. This study thus contributes to the existing research on the relationship between brain activity and cognitive functions by showing which brain activities need to be supressed and which ones need to be enhanced. Knowing how brain activity affects cognitive functions is vital in neuroscience and computer science as it forms the foundation for developing BCI-based solutions that can be used to enhance the cognitive functions required for improving mathematics aptitudes. The next section provides practical recommendations based on the findings of this study.

6.6. Practical Recommendations for Addressing Math Crisis

Based on the findings of this study, several practical recommendations are made that can contribute to the amelioration of the math crisis in South Africa. The first practical recommendation is a call for schools to develop strategies of enhancing cognitive functions among learners. Smith and Hardman (2014) have explicated that most South African schools have computers, but they are not being used effectively in developing the cognitive functions of the learners. This study provided empirical evidence that cognitive functions can be developed and enhanced. Since 2011 more than 353 ICT-enabled mathematics laboratories have been built in schools across South Africa (Siswana, 2014). Each of these mathematics laboratories cost several hundred thousand Rands to make it operational. The impact of these mathematics laboratories on addressing the math crisis can be improved by allocating some of the funds to technologies and software that can be used to develop cognitive functions. With technologies like BCI-based systems, teachers can objectively evaluate the cognitive functions of learners and identify thoses who need additional cognitive training. Learners could regularly use such systems, as well as game-based software, that enhance cognitive functions.

Secondly, it was observed that increased Gamma brain activity had a negative influence on cognitive functions. Gruber and Muller (2002) showed that Gamma activity could be reduced with recurrent presentations of the same visual stimulus. This explains why continuous learning of mathematics concepts reduces math anxiety, as explicated by Jansen *et al.* (2013). Consequently, teachers and parents/guardians should try to continuously expose learners to mathematics exercises as much as possible as this will decrease the high Gamma brain activity that is disruptive for cognitive function development. Learners with high maths anxiety always shy away from attempting mathematics problems (Mohamed & Tarmizi, 2010; Zakaria *et al.*, 2012). However, if they are encouraged to continuously study and attempt mathematics exercises, it will reduce the high Gamma activity that accounts for the anxiety-like behaviour, and this will in turn increase their confidence and attitudes towards mathematics.

Thirdly, Alpha and Beta brain activity were seen to have a significant positive influence on cognitive functions. As such, teachers and parents can engage their children in activities that augment the power of Alpha and Beta brain activities in an attempt to develop a solid basis for enhancing their cognitive functions. With regards to Alpha brain activity, learners can engage in the “eyes open Alpha power training” proposed by Dekker, Van den Berg, Denissen, Sitskoorn and Van Boxtel (2014). This training entails using a headphone with mounted electrodes that provide EEG feedback while the participants listen to their favourite music. This is done wth eyes open, followed by eyes closed. The authors demonstrated that the training could significantly improve a person's baseline Alpha brain activity power. For enhancing the power of Beta brain activity, the maximal exercise proposed by Moraes *et al.* (2007) can be adopted as it showed significant increases in Beta activity. The proposed approach includes resting for eight minutes with eyes closed, to be followed by an intensive exercise of about 30 minutes with the use of a mechanical cycle ergometer.

Lastly, this study contributed to the existing evidence that cognitive functions have a significant impact on mathematics performance. Although this study focused on a small sample of learners in South Africa, the proposed approach can be adopted and applied to the broader South African context. It is therefore recommended that schools should develop strategies and practical methods to enhance cognitive functions. Kloppers and Grosser (2010) had proposed that lecturers who train educators in South Africa should adopt the FIE strategy for enhancing the cognitive functions of the educators. The FIE strategy includes a fully designed classroom curriculum that has been specifically established for enhancing cognitive functions. This should be taken seriously as evidence indicates that the attitudes of the educator towards mathematics translate to the students. For example, studies (Furner & Gonzalez-DeHass, 2011; Shields, 2006) have shown that when teachers have high levels of math anxiety, the anxiety is transferred to the learners. Also, resources should be directed towards training educators in programs that enhance cognitive functions, such as CBGT. Furthermore, recently developed solutions such as the Physical Activity Program (Verret, Guay, Berthiaume, Gardiner, & Beliveau, 2012) and the Kinect-based system (Kayama *et al.*, 2014) can be adopted in South African schools as a means of enhancing the learners' cognitive functions.

6.7. Limitations of the Study and Recommendations for Future Studies

Although this study adopted a systematic and well thought-out research design for evaluating the change process (in this case changes in selected cognitive functions) as established by prior studies (Karapanos *et al.,* 2009; Karapanos *et al.*, 2010; Singer & Willett, 2003; Rieger, 2009; Combaz *et al.,* 2013; Tullis & Albert, 2013), it is not without limitations.

Firstly, the study adopted a within-subjects design with eight data gathering waves to ascertain changes in the participant's level of cognitive functions across two sessions that took place on separate days. During each task, two types of feedback were provided to the participant (i.e. real-time biofeedback, and feedback after task). While evidence suggests that feedback contributes to effective learning (Ávila, Chiviacowsky, Wulf & Lewthwaite, 2012; Chiviacowsky & Wulf, 2007), it is not possible at this stage to identify the impact each of the feedback types had on the cognitive functions. Understanding how real-time feedback and feedback after task impact on cognitive functions can go a long way to improve the design of BCI-based system for optimal cognitive function training. To address this situation going forward, future studies can utilize a control group that does not view the real time feedback on cognitive functions from the BCI (e.g. visual feedback when the level of math anxiety increases from its current state). Also, a control for the overall feedback on cognitive functions for each task presented at the end of the task can be examined to determine its effect on controlling and training the cognitive functions. Since this study was a proof of concept on using a BCI-based solution for training and enhancing cognitive functions, the general assumption adopted from existing studies (Ávila, *et al.,* 2012; Chiviacowsky & Wulf, 2007) was that effective feedback will improve the participants' learning on how to train the cognitive functions. As such both types of feedback available were combined. In order to improve the effectiveness of using a BCI-based solution for enhancing cognitive functions, future studies can investigate this association further by using various types of visual feedback, as well as using control groups to provide a more detailed insight in the identified relationships.

Secondly, this study showed that cognitive functions had a significant impact on mathematics performance. While the findings are congruent with existing studies from the developed world, the small sample used makes it difficult to generalize the results to all learners in South Africa. Nonetheless, it was interesting to observe significant similarities between the BCI-based measures of cognitive functions and the subjective measures captured with the well-established neuropsychological questionnaires. As such, studies in other parts of the country should use the questionnaires for the different cognitive functions and capture data for a wider sample so as to better generalise the findings on the impact of cognitive functions on mathematics performance in South Africa. For example, Hlalele (2012) and Mutodi and Ngirande (2014) have examined the level of math anxiety in South African schools, however, the impact of math anxiety on mathematics performance was not examined. This is, therefore, an avenue for future research to expand on the findings of this study on a larger scale.

Lastly, this study focused only on one type of non-invasive commercially available BCI device (i.e. Emotiv EPOC). Consequently, the findings are limited to this particular BCI device and cannot be generalized for all non-invasive commercially available BCIs. Future studies can, therefore, use other available BCI devices, such as the Nerurosky-Mindset and Enobio, to determine if the significant findings obtained from this study can be replicated. Furthermore, some of the cognitive functions and brain activities captured with the aid of the Emotive EPOC showed significant correlations with usability and user experience measures. Future studies can use other BCI devices to underpin these relationships in different context and thus provide a new approach of examining usability and user experience.

6.8. Chapter Summary

This chapter provided conclusions and recommendations drawn from this dissertation. Firstly, an overview of the study was provided to give the reader a quick recap of the main aspects covered in the study. Thereafter conclusions were drawn regarding the four hypotheses established in the study, as well as discussions on how the objectives of the study were achieved. Next, a detailed conclusion on the significance of the study was provided based on the key findings of the research. Immediately following that was the practical recommendations that can be applied to address the math crisis in South Africa. Lastly, the limitations of the study and recommendations for future studies were provided.

This study has provided empirical evidence to support the use of BCI technologies for educational purposes, specifically in the domain of enhancing cognitive functions. Given that cognitive functions have been widely known to have a statistically significant impact on mathematics attitudes and performance, any successful attempt to enhance cognitive functions in South Africa can go a long way to address the current math crisis.

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APPENDICES

Appendix A: Letters for Parents/Guardians

To whom it may concern

My name is Silas Verkijika and I am currently busy with a Master's dissertation in Computer Information Systems that aims to examine the use of a brain-computer interface (BCI) in enhancing cognitive functions for Mathematics development.

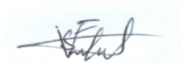
To achieve this goal, I have developed a mathematics educational game that uses BCI to capture and monitor the game player's cognitive functions. This study aims at providing valuable neuro-feedback that can enable the users of the application to better understand their cognitive skill and develop them further. Cognitive skills such as inhibitory control, working memory, mathematics anxiety, and number sense have been proven to be the building blocks of mathematics skills from childhood to adulthood. As a contribution to the solutions required for addressing the current "math crisis" in South Africa, this study intends to examine how Computer Science can play a major role through the use of a BCI.

We wish to seek your collaboration in getting participants for this study. The desired participants are children from the age groups of 9 to 16 years. Parents/guardians of the children are required to give informed consent before their children can participant in the study. Also, the parents/guardians are welcome to accompany their children throughout the study. We guarantee that the study poses no harm to the participants. For parents/guardians interested in allowing their children to participate in the study, further details about the project can be obtained from the researchers using the contact details below.

Supervisor:

Dr Lizette de Wet
Tel: 051 4013705/0825624117
Lizette@ufs.ac.za

Student



Mr. SF Verkijika
Tel: 0782208877
Email: vekasif@gmail.com

Appendix B: Information Sheet and Consent Form

Information Sheet

Title of Research Project: Assessing the Use of a Brain-computer Interface in Mathematics Education: The Case of a Cognitive Game

Student Name: SF Verkijika
Supervisor: Dr Lizette De Wet
Purpose of the Test

This test is part of my master's thesis which aims at determining if a brain-computer interface (BCI) device can be used for enhancing cognitive functions for mathematics development. To achieve this goal, the Emotiv BCI device will be used for playing a mathematics educational game. Pre-test and post-test scores will be used for determining the impact of the BCI on the participant' cognitive functions. Also, the Emotive BCI will be used to capture the user's physiological data. The physiological data will be used to explain things like math anxiety and usability issues regarding the software application. The types of physiological data captured by the Emotive include: excitement, engagement, meditation and frustration.

The participant's Responsibilities

The participant will be required to complete a pre-test and post-test interview/questionnaire. The pre-test interview/questionnaire will gather the participant's demographic information as well as measure his/her current level of cognitive functions. The post-test interview/questionnaire will be used to gather information on the cognitive functions to determine the level of change on such functions since the participant was introduced to the BCI mathematics game. The participant will be required for two 30 minute long sessions that take place on two separate days prearranged with the participant based on availability. For each session, the participant will be guided by the researcher in a thirty minutes game play session with the Emotiv EPOC. Also, the participant can withdraw at any time without giving and reason.

Treatment or the participant's information

All the data will be collected anonymously and no record will be linked directly to the name of the participant. A high level of confidentiality will be maintained to ensure that only authorized persons have access to the data. Also, the data will be used strictly for the purpose of this study and no identifiable information will be published that can link back to a particular user.

Contact Details: For more information, contact Dr Lizette De wet, Tel: 051 4013705; email:

lizette@ufs.ac.za

Agreement: Turn to the agreement below to sign if you are willing to allow your child to participate in this study.

Reward: Each participant will be rewarded for their time with a R50 Kloppers or Checkers voucher (based on participant preference) and a chocolate bar. The Emotive EPOC is non-invasive and poses no risk to the participant. At this stage, we do not however guarantee any immediate benefits to the participants' cognitive functions as this is a testing phase.

N.B: In participating in this study, the participant will be helping in addressing a critical need in South Africa which is to overcome the "math crisis" with the aid of technology.

Reference Number: ___________

CONSENT FORM

Title of Project: **Assessing the Use of a Brain-computer Interface in Mathematics Education: The Case of a Cognitive Game**

Mark an X on the boxes

1. I confirm that I have read and understand the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. ☐

2. I understand that my child's participation is voluntary and that he/she is free to withdraw at any time without giving any reason. ☐

3. I understand that the information gathered from the test will be used strictly for the purpose of the study and handled with a high level of confidentiality and anonymity. ☐

4. I agree that my child should take part in the above study. ☐

________________	______________	______________
Name of Parent/Guardian	Date	Signature
________________	______________	______________
Name of Researcher	Date	Signature

Contact number of parent/guardian: ____________________________________

Appendix C: Pre-Test Questionnaire

Reference Number_______________

User Information and Cognitive Functions Questionnaire

The purpose study is to investigate the impact of a BCI mathematics game on cognitive functions. This questionnaire aims at gathering information about your personal experiences in relation to various cognitive functions. Also, demographic and computer/BCI usage information are requested in the questionnaire. Please complete the questions to reflect your opinions as accurately as possible and to answer factual questions to the best of your knowledge.

Your responses will be entirely anonymous and the information will be kept strictly confidential. Also, your participation is entirely voluntary.

For each question, where appropriate, please indicate the correct answer by marking an "X" on the corresponding number.

1. Personal Information

1.1 Contact number: ____________________________ (parent/Guardian)

1.2 Age:

9-Years	10- Years	11-Years	12-Years	13-Years	14-Years
1	2	3	4	5	6

1.3 Gender:

Male	1	Female	2

1.4 Grade: __________

1.5 Home language:

Afrikaans	English	Sotho	Xhosa	Zulu	Others
1	2	3	4	5	6
If others, specify:					

2. Computer Usage

2.1. For how many years have you been using a computer?

Never	1	2 – 3 years	4
< 6 months	2	4- 6 years	5
6 months – 1 year	3	> 6 years	6
If your answer to question 2.1 is "Never", then Skip to question 3.1 below.			

2.2. How often do you use a computer:

Daily	1	Few times a month	4
More than 2 times a week	2	Few times a year	5
1-2 times a week	3	Seldom	6

2.3.What activities do you use a computer for?

Social networking(e.g. Facebook, Twitter)	1	Playing Games	4
Studying (e.g. researching a school assignment)	2	Shopping	5
Surfing the internet(e.g. Email)	3	Other	6
If other, Please Specify:			

3. Brian computer interface usage

3.1. Have you used a BCI before?

Yes	1	No	2

3.1.1 If yes, how many times have you used it ____________

3.1.2. What did you use the BCI for?

____

____

____

4. Working Memory (WMQ)

Statement	No t at all	A littl e	Moderatel y	A lo t	Extremel y
Central Executive					
4.1 Do you find it difficult to describe a step-by-step activity? For example, giving road directions.	1	2	3	4	5
4.2 When you are carrying out an activity, if you realise that you are making a mistake, do you find it difficult to change strategy?	1	2	3	4	5
4.3 Do you have difficulty in remembering what homework you have to do each day?	1	2	3	4	5
4.4 Do you find that you hesitate for a long time before choosing what you want in a shop?	1	2	3	4	5
Visuospatial Memory					
4.5 Do you need to make an effort to concentrate in order to follow a conversation in which you are participating with many other people?	1	2	3	4	5
4.6 When you are interrupted during an activity by a loud noise (door slam, car horn) do you have difficulty in getting back to the activity?	1	2	3	4	5
4.7 Do nearby conversations disturb you during a conversation with another person?	1	2	3	4	5
4.8 Do you find it difficult to carry out an activity in the presence of background noise (traffic, radio or television)?	1	2	3	4	5
4.9 Do you find that you get tired quickly during an activity which demands a lot of attention (for example, reading, or solving mathematics problems)?	1	2	3	4	5
Storage Memory					
4.10 D o you have problems with remembering sequences of numbers, for example, when you have to note down a telephone number?	1	2	3	4	5
4.11 D o you find it difficult to remember the name of a person who has just been introduced to you?	1	2	3	4	5
4.12 D o you have difficulty remembering what you have read?	1	2	3	4	5
4.13 D	1	2	3	4	5

o you need to re-read a sentence several times to understand what it says?					
4.14 If somebody speaks quickly to you, do you find it difficult to remember what you were told or asked?	1	2	3	4	5

5. Math Anxiety (FSMAS)

Statement	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
5.1 Mathematics does not scare me at all.	1	2	3	4	5
5.2 It would not bother me at all to take more mathematics courses.	1	2	3	4	5
5.3 I usually do not worry about my ability to solve mathematics problems.	1	2	3	4	5
5.4 I have always been at ease during mathematics tests.	1	2	3	4	5
5.5 Mathematics makes me feel uncomfortable and nervous.	1	2	3	4	5
5.6 I always feel tense when I think of trying hard mathematics problems.	1	2	3	4	5
5.7 My mind goes blank and I am unable to think clearly when working mathematics.	1	2	3	4	5
5.8 Mathematics makes me feel uneasy and confused.	1	2	3	4	5

6. Inhibitory Control (EATQ)

For each statement, please circle the answer that best describes how true each statement is for you. There are no best answers. People are very different in how they feel about these statements. Please circle the first answer that comes to you. You will use the following scale to describe how true or false a statement is about you:

Circle number:	If the statement is:
1	Almost always untrue of you
2	Usually untrue of you
3	Sometimes true, sometimes untrue of you
4	Usually true of you

5	Almost always true of you

Statements on inhibitory control					
6.1 It is hard for me not to open presents before I am supposed to.	1	2	3	4	5
6.2 When someone tells me to stop doing something, it is easy for me to stop	1	2	3	4	5
6.3 The more I try to stop myself from doing something I should not do, the more likely I am to do it.	1	2	3	4	5
6.4 It is easy for me to keep a secret.	1	2	3	4	5
6.5 I can stick with my plans and goals.	1	2	3	4	5

7. Number Sense (NST)

Mark the correct answer with an "X"

Which fraction is closer to $\frac{1}{2}$	$\frac{3}{8}$	$\frac{7}{12}$	$\frac{4}{2}$	$\frac{6}{3}$
Without calculating the exact answer, chose the best estimate for $\frac{5}{4}+\frac{7}{8}$	1	2	6	9
Which fraction is the biggest	$\frac{8}{15}$	$\frac{7}{9}$	$\frac{1}{5}$	$\frac{3}{8}$
Chose the correct sign: 8____2 = 6	+	-	×	÷
Chose the correct sign: 12____3 = 4	+	-	×	÷

Thank you for completing the questionnaire!!

Appendix D: Post-Task Questionnaire

First Non-BCI Game Task

After-Scenario Questionnaire										
1.1	Overall, I am satisfied with the ease of playing the game in this task.	strongly disagree	1	2	3	4	5	6	7	strongly agree
1.2	Overall, I am satisfied with the colors used in the game as well as the general look and feel of the game.	strongly disagree	1	2	3	4	5	6	7	strongly agree
1.3	Overall, I enjoyed playing the game	strongly disagree	1	2	3	4	5	6	7	strongly agree

Second Non-BCI Game Task

After-Scenario Questionnaire										
2.1	Overall, I am satisfied with the ease of playing the game in this task.	strongly disagree	1	2	3	4	5	6	7	strongly agree
2.2	Overall, I am satisfied with the colors used in the game as well as the general look and feel of the game.	strongly disagree	1	2	3	4	5	6	7	strongly agree
2.3	Overall, I enjoyed playing the game	strongly disagree	1	2	3	4	5	6	7	strongly agree

Thank you for completing the questionnaire!!

Appendix E: Post-Test Questionnaire

Reference Number_______________

Usability Questionnaire

The purpose study is to investigate the impact of a BCI mathematics game on cognitive functions. This questionnaire aims at gathering information about your personal experiences from the interaction with the BCI mathematics game. Please complete the questions to reflect your opinions as accurately as possible and to answer factual questions to the best of your knowledge.

Your responses will be entirely anonymous and the information will be kept strictly confidential. Also, your participation is entirely voluntary.

For each question, where appropriate, please indicate the correct answer by marking an "X" on the corresponding number.

1. Game Engagement/Experience Questionnaire (GEQ)

Statement	Strongly Disagree				Strongly Agree
1.1 Things seem to happen automatically	1	2	3	4	5
1.2 I feel different	1	2	3	4	5
1.3 I feel scared when I do not know what to do	1	2	3	4	5
1.4 The game feels real	1	2	3	4	5
1.5 If someone talks to me, I do not hear them	1	2	3	4	5
1.6 Time seems to kind of standstill or stop	1	2	3	4	5
1.7 I did not feel tired	1	2	3	4	5
1.8 My thoughts go fast	1	2	3	4	5
1.9 I lose track of where I am	1	2	3	4	5
1.10 I play without thinking about how to play	1	2	3	4	5
1.11 Playing makes me feel calm	1	2	3	4	5
1.12 I really get into the game	1	2	3	4	5
1.13 I feel like I just can't stop playing	1	2	3	4	5

2. System Usability Scale (SUS) Questionnaire

Statement		Strongly Disagree				Strongly Agree
2.1 I would like to use this tool frequently	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.2 I found the tool unnecessarily complex.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.3 The tool was easy to use.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.4 I would need the support of a technical person to be able to use this tool.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.5 I found the various functions in this system were well integrated.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.6 I thought there was too much inconsistency in this system	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.7 I would imagine that most people would learn to use this system very quickly.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.8 I found the system very cumbersome to use.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.9 I felt very confident using the system	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5
2.10 I needed to learn a lot of things before I could get going with this system.	**BCI**	1	2	3	4	5
	Game	1	2	3	4	5

3. Questionnaire for User interface Satisfaction (QUIS)

Overall Reaction to Software														**NA**
3.1		Terrible	0	1	2	3	4	5	6	7	8	9	Wonderful	
3.2		difficult	0	1	2	3	4	5	6	7	8	9	easy	
3.3		Frustrating	0	1	2	3	4	5	6	7	8	9	satisfying	
3.4		dull	0	1	2	3	4	5	6	7	8	9	stimulating	
3.5		rigid	0	1	2	3	4	5	6	7	8	9	flexible	
Screen														
3.6	Reading characters on screen	hard	0	1	2	3	4	5	6	7	8	9	easy	
3.7	Organization of information	Confusing	0	1	2	3	4	5	6	7	8	9	Very clear	
System Capabilities														

3.8	System speed	Too slow	0	1	2	3	4	5	6	7	8	9	Fast enough	
3.9	System tends to be	Noisy	0	1	2	3	4	5	6	7	8	9	Quiet	
3.10	Correcting your mistakes	difficult	0	1	2	3	4	5	6	7	8	9	easy	

4. Survey of Technology Use (SOTU)

Goal : **To increase my Mathematics skills**					
	No	**somewhat**			**Yes**
4.1 Do you understand the goal written above	1	2	3	4	5
4.2 Do you feel you can achieve this goal	1	2	3	4	5
	Not Much	**Somewhat**			**A lot**
4.3 How much do you want to achieve this goal?	1	2	3	4	5
	No	**Maybe**			**Yes**
4.4 Do you prepare to learn from listening to a teacher's lecture or by playing an educational game	1	2	3	4	5
4.5 Have you ever experienced this type of technology or this method?	1	2	3	4	5
4.6 Have you observed others using this technology/method?	1	2	3	4	5
Which statements below that describe you?				**Yes**	**No**
4.7 I am curious & excited about new things				1	2
4.8 I often want to work slower than others				1	2
4.9 I sometimes feel intimidated by technology				1	2
4.10 I am impatient				1	2
4.11 I want to control my own learning space				1	2
4.12 I am often easily distracted				1	2
4.13 I prefer to work in a group than by myself				1	2

5. Usefulness, Satisfaction, and Ease of use questionnaire

Statement	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
5.1 The BCI device was easy to use	1	2	3	4	5
5.2 The game was easy to play	1	2	3	4	5

5.3 This application can be useful in helping me to learn mathematics	1	2	3	4	5
5.4 I can play the game without written instructions	1	2	3	4	5
5.5 It is easy to learn how to play the game	1	2	3	4	5
5.6 I am satisfied with the application	1	2	3	4	5
5.7 I would recommend it to a friend.	1	2	3	4	5
5.8 It is fun to use	1	2	3	4	5
5.9 It is pleasant to use	1	2	3	4	5

Thank you for completing the questionnaire!!

Appendix F: Ethical Clearance

Faculty of Natural and Agricultural Sciences

24-Oct-2014

Dear Mr Silas Verkijika

Ethics Clearance: Assessing the Use of a Brain Computer Interface (BCI) in Mathematics Education: The Case of a Cognitive Game

Study Leader/Supervisor: De Wet, Lizette

Principal Investigator: Mr Silas Verkijika

Department: Computer Science and Informatics (Bloemfontein Campus)

This letter confirms that a research proposal with tracking number: **UFS-HSD2014/0411** and title: **'Assessing the Use of a Brain Computer Interface (BCI) in Mathematics Education: The Case of a Cognitive Game'** was given ethics clearance by the Ethical Committee.

Please ensure that the Ethical Committee is notified should any substantive change(s) be made, for whatever reason, during the research process. This includes changes in investigators. Please also ensure that a brief report is submitted to the Ethical Committee on completion of the research. The purpose of this report is to indicate whether or not the research was conducted successfully, if any aspects could not be completed, or if any problems arose that the Ethical Committee should be aware of.

Note:
1. This clearance is valid from the date on this letter to the time of completion of data collection.
2. Progress reports should be submitted annually unless otherwise specified.

Yours Sincerely

Prof. Neil Heideman
Chairperson: Ethical Committee
Faculty of Natural and Agricultural Sciences

Appendix G: Research Output

Using a Brain-Computer Interface (BCI) in Reducing Math Anxiety: Evidence from South Africa

Verkijika, SF & De Wet, L.

Computers & Education, 81, 113-122.

Abstract

Prior studies have indicated that learning mathematics is highly associated with attitudes towards mathematics and emotions like math anxiety. Over the years, strong empirical evidence has emerged, showing that math anxiety has a significant negative effect on mathematics performance. Interestingly enough, some researchers have shown that math anxiety can be trained and reduced. However, the proposed interventions have mostly focused on teachers as oppose to students, while the existing physiological approaches like cognitive behavioural therapy require administration by trained professionals. With recent advancements in technology, low cost commercial brain-computer interface (BCI) devices that can capture human emotions in real time have been developed and can have a potential use in training and reducing math anxiety. In this study, the objective was to determine if using a BCI mathematics educational game can help students to effectively reduce math anxiety. To attain this objective, a within-subjects longitudinal research design with eight data gathering waves was adopted as the primary methodology to ascertain changes in the participant's level of math anxiety across two sessions that took place on separate days. Analysis of data captured across two training sessions with a BCI mathematics educational game showed that math anxiety can be effectively trained and reduced with a BCI. In addition, the results showed that math anxiety has a significant negative impact on mathematics performance which is congruent with prior studies. These findings provide a novel way in which a low cost non-invasive BCI device can be used for educational purposes.

Keywords: brain-computer interface, math anxiety, computer educational game, mathematics performance

1. Introduction

Understanding the relationship between emotions and learning has gained enormous grounds over the years. Prior research (Sabourin & Lester, 2014; Sun & Pyzdrowski, 2009) has indicated that emotions play a vital role in fostering the cognitive functions that are important for learning. Empirical evidence indicate that positive emotions such as engagement and concentration can enhance learning (Kanfer & Ackerman, 1989; Pekrun, Goetz, Titz & Perry, 2002; Sabourin & Lester, 2014), while negative emotions such as frustration, anxiety, and boredom have an adverse effect on learning (Meyer & Turner, 2006; Sabourin & Lester, 2014). The development of low cost commercial off-the-shelf BCIs has provided great opportunities for studying and understanding human emotions. A BCI is a communication system for controlling an electronic device (e.g. a computer) based on user evoked bio-potentials. These BCIs are becoming an essential component in understanding how affective computing can enhance education. One important educational discipline in which affective computing can play a vital role is in mathematics education.

Learning mathematics is strongly associated with attitudes towards mathematics and emotions like math anxiety (Jansen, Louwerse, Straatemeier, Van der Ven, Klinkenberg & Van der Maas, 2013; Sun & Pyzdrowski, 2009). Ashcraft and Krause (2007) define math anxiety as a "feeling of tension, apprehension, or fear that interferes with math performance" (p.243). The findings of most studies (Zakaria, Zain, Ahmad & Erlina, 2012; Ashcraft & Krause, 2007; Jansen *et al.*, 2013) have clearly indicated a significant negative relationship between math anxiety and mathematics performance. According to Zakaria *et al.* (2012) math anxiety is an important physiological dimension of learning that every educator must try to identify in his/her students. However, math anxiety is still very dominant around the globe. For example, about 93% of Americans experience some form of math anxiety (Furner & Duffy, 2002; Scarpello, 2007). Studies in South Africa (Mutodi & Ngirande, 2014; Hlalele, 2012) have noted that while the country faces a serious crisis of mathematics education, affective components of learning such as math anxiety have been overlooked. These researchers further documented that there is a very high level of math anxiety among learners in South Africa. As such, one way of addressing the maths crisis in South Africa is by developing approaches to reduce the high levels of math anxiety.

Studies (Cates & Rhymer, 2003; Kazelskis & Reeves, 2002; Lim & Chapman, 2013; Mattarella-Micke, Mateo, Kozak, Foster & Beilock, 2011; Medeiros & Leclercq, 2007) in cognitive psychology and mathematics education have measured math anxiety using subjective measures such as the Fennema-Sherman Mathematics Anxiety Scale (FSMAS) and objective measures such as physiological arousal. Physiological arousal can be measured in real-time with a BCI device which could be useful in measuring and controlling anxiety levels. According to

Sun & Pyzdrowski (2009) teachers can use several strategies in the classroom to reduce maths anxiety, however, when students are faced with math anxiety on their own, they often do not know what to do. One effective means through which students learn mathematics independently is through mathematics educational games (Devlin, 2011; Abdullah, Bakar, Ali, Faye & Hasan, 2012). Combining mathematics computer games with the potential of the BCI device in providing real-time neuro-feedback on physiological arousal can act as a technological solution for effectively monitoring, training, and reducing math anxiety.

The use of educational games for enhancing mathematics skills has shown an enormous potential. However, researchers (Mitchell & Savill-Smith, 2004; Kebritchi, Hirumi & Bai, 2010) have highlighted that there is still a high shortage of empirical studies to support the effectiveness of mathematics educational computer games. Also, some existing empirical studies have yielded mixed results (Godfrey & Stone, 2013; Laffery, Espinsosa, Moore & Lodree, 2003), and most novel computer games (e.g. BCI based games) are yet to be tested. The existing empirical evidence has focused on post-game mathematics test for evaluating the impact of the game while little has been done on actually evaluating the impact of the games on the affective components of learning (e.g. anxiety, frustration, engagement etc.), which the players experience during gameplay.

This is a gap that needs to be filled since affective components of mathematics such as math anxiety have been established to explain the differences in math skills from early childhood to adulthood (Zakaria *et al.,* 2012; Ramirez, Gunderson, Levine & Beilock, 2013). Lyons and Beilock (2012) emphasized that educational interventions that focus on controlling negative emotional responses to math stimuli (e.g. math anxiety) will be more effective than simply providing additional mathematics training. Several studies (Gresham, 2007; Hendel & Davis, 1978; Tooke & Lindstrom, 1998) have shown that math anxiety can be reduced through training and education; however, the studies have mostly focused on teachers rather than students. Furthermore, a few studies (Karimi & Venkatesan, 2009; Scneider & Nevid, 1993; Sharp, Colthar, Hurford & Cole, 2000) have adopted psychological interventions to provide an emotional response approach to reducing math anxiety. For example Sharp *et al.* (2000) showed that relaxation training significantly reduced math anxiety; Karimi and Venkatesan (2009) using cognitive behavioural group therapy (CBGT) also showed that it significantly reduced math anxiety; while Scneider and Nevid (1993) showed that stress management training and systematic desensitization lowered the math anxiety of college students. While these studies provide promising results, implementation in a larger context is difficult as the programs need to be administered by trained professionals who are often scarce especially in developing countries. In this light, this study looks at a psychological approach to learning that incorporates recent technology and can be administered by the students themselves or their parents/guardians in training, controlling and reducing their math anxiety levels. As such, this study has as main focus to determine if using a BCI mathematics educational game can help students to effectively reduce math anxiety.

2. Overview of BCI technology

Wolpaw and Wolpaw (2012) define a BCI as a communication system in which the commands or messages sent by an individual to the external world do not pass through the normal output channels of brain communication such as peripherals (e.g. speech) and muscles (e.g. gestures). Instead, a BCI device uses any bio-potentials that are under the conscious control of the user (Gnanayutham & George, 2006). Bio-potentials are electrical signals that originate from the brain and nervous system (Colman & Gnanayutham, 2013). BCIs establish a direct connection between the brain and an electronic device (Kübler and Müller, 2007). This direct communication between the brain and a computer is achieved by decoding brain signals into commands that can be understood by the computer. BCIs can either be invasive or non-invasive. Invasive BCIs require surgical removal of a section in the skull where the brain underneath needs to be accessed, while non-invasive BCIs decode brain signals using scalp recordings (EEG-based BCIs)[7] and as such do not require any surgery or medical care. Figure 1 shows an overview of how the components of a BCI system function together.

[7] EEG stands for electroencephalography and refers to the measurement of electrical waves generated by the brain

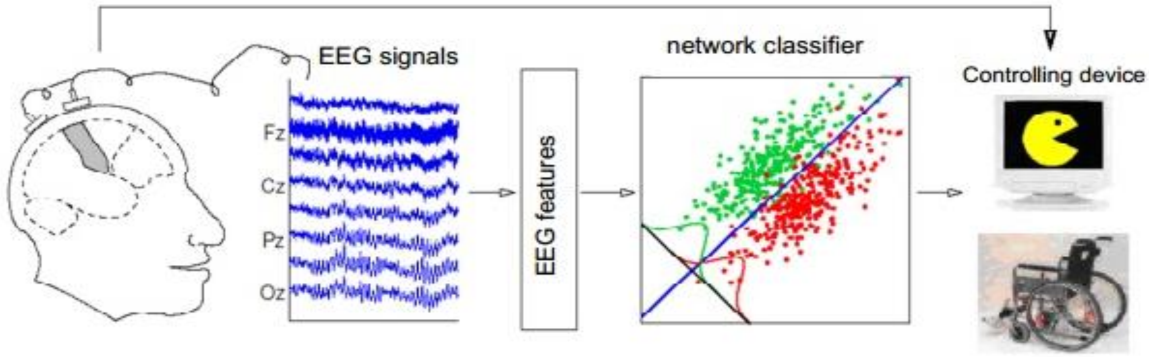


Figure 1: Schematic view of BCI system components (Source: Karlovskiy and Konyshev, 2007)

This study will make use of the Emotive EPOC BCI which is a low cost non-invasive EEG-based BCI that has gained popularity in recent years. Researchers (Duvinage, Castermans, Petieau, Hoellinger, Cheron & Dutoit, 2013; Badcock, Mousikou, Mahajan, de Lissa, Thie & McArthur, 2013; Taylor & Schmidt, 2012) have adopted the Emotiv EPOC to examine several BCI paradigms; however, little has been done with regards to its potential for educational purposes. The Emotiv EPOC neuro-headset comes with a control panel equipped with three detection applications namely: the Cognitiv Suite (captures cognitive actions for BCI-like control), Expressiv Suite (captures user's facial expressions), and the Affectiv Suite (captures information on the user's emotional states). All these application suites capture user information in real-time. Only anxiety data from the Affectiv Suit is reported for the purpose of this study.

3. Computer games and mathematics education

Digital educational games have been widely used over the years as a means for enhancing the mathematics skills of learners. According to Oblinger (2006) computer games have been recognized as important tools for mathematics education because they provide an effective and fun learning environment. Over the past decade, many researchers and academics have started to pay special attention to the impact that computer games could have on improving mathematics performance in schools (Kim & Chang, 2010; Oblinger, 2006; Ke & Grabowski, 2007). However, many studies have failed to find consensus on the impact of computer games on mathematics skill development. Some studies (Bragg, 2012; Bokyeong, Hyungsung, & Youngkyun, 2009; Lopez-Moreto, & Lopez, 2007; Burguillo, 2010; Kebritchi *et al.*, 2010; Shin, Sutherland, Norris, Soloway, 2012) have found significant evidence to support the use of computer games for mathematics education, while others (Nusir, Alsmadi, Al-Kabi & Sharadgah, 2012; Vos, Van der Meijden & Denessen, 2011; Lim, Nonis & Hedberg, 2006) have had mixed results or no impact. These studies have, however, focused primarily on the post-game mathematics test results without evaluating the possible effect that emotions during the game play could have on influencing the mathematics outcome. As such, a key affective component like math anxiety which accounts for significant difference in math performance has been neglected.

4. Math anxiety and mathematics performance

Most students who are weak in mathematics always worry a lot in the process of solving mathematics problems and this aspect of worrying is the key factor that makes them perform poorer (Mohamed & Tarmizi, 2010). Generally, people tend to forget mathematics equations and lose confidence when they are experiencing math anxiety. The findings of most studies (Zakaria *et al.,* 2012; Ashcraft and Krause, 2007; Jansen *et al.,* 2013; Ramirez *et al.,* 2013) have clearly indicated a negative relationship between math anxiety and mathematics performance. As math anxiety increases, the level of math performance decreases. Tapia and Marsh (2002) further indicated that students who have low levels of math anxiety are more confident, excited, and highly motivated to learn mathematics more than students with high levels of math anxiety. Jansen *et al.* (2013) established that mathematics performance only increases with more practice. This explains why people with high math anxiety tend to perform poorer in mathematics as the anxiety causes them to avoid solving mathematics problems as established by Zakaria *et al.* (2012). It is therefore of prime importance to identify students with high math anxiety and try to help them build their confidence in solving mathematics problems.

The relationship between math anxiety on mathematics performance has been consistent for both 'trait math anxiety' (Miller & Bichsel, 2004; Ganley & Vasilyeva, 2011) and 'state math anxiety' (Beilock, Rydell & McConnell, 2007; Brodish & Devine, 2009). Trait math anxiety refers to the general tendency of feeling anxious about mathematics while state math anxiety is a measure of anxiousness during a mathematics testing situation. In a longitudinal study comprising of 113 grade two and three children, Vukovic, Kieffer, Bailey and Harari (2013) established that math anxiety was responsible for significant difference in mathematics performance. Ramirez *et al.* (2013) using 164 grade one and two children found that there was a negative relationship between math anxiety and mathematics achievement. The relationship showed that children with high levels of math anxiety had poorer mathematics achievement than those with low math anxiety.

Cates and Rhymer (2003) used the FSMAS to classify students according to low and high math anxiety levels and then administered the two groups with a timed mathematics test comprising of basic operations like addition, multiplication, division and subtraction. The findings from the study revealed that students with high math anxiety performed poorer in all the different mathematic operations.

One way in which math anxiety affects mathematics performance is by interfering with the functioning of the working memory, which is a key cognitive function that significantly affects mathematics performance. Vukovic *et al.* (2013) highlighted that mathematics anxiety affected how some students used working memory resources in solving mathematics problems. Ramirez *et al.* (2013) also explicated that math anxiety in first and second graders negatively affected students working memory resulting in lower mathematics performance.

5. Methodology

5.1. Participants

This study adopted a convenience sampling in recruiting participants. A prerequisite for participating in the study was for the participant to be from the age group of 9 to 16 years inclusive. Parents/guardians of learners were contacted to find out if they were interested in allowing their children to participate in the study. Through this process, 36 children were available as participants. The majority of the participants were female (52.8%). The youngest participant was 10 years old and the eldest was 16 years. The average age of the participants was 14.06 years with a standard deviation of 2.08.

5.2. Materials

The research edition of the Emotiv EPOC BCI device was used in this study. A BCI mathematics educational game called Math-Mind (Figure 2 and 3) was developed by the researchers and used for the purpose of this study. The participants played the game while wearing the BCI headset. The Math-Mind game captured real-time brain activity with the Emotiv EPOC BCI and provides visual feedback to the user when anxiety levels increased in an attempt to help the user control the anxiety levels. The Math-Mind game was developed using XNA 4.0 and was administered to the participants using a Core i3 Acer Laptop with 4Gig RAM. The participants completed a pre-test questionnaire which captured demographic information and information relating to their math anxiety levels based on the widely used FSMAS math anxiety scale.

Figure 2: Screen shot of the Math Mind Game

Figure 3: Screen shot of Math-Mind game with real time feedback indicating a high level of math anxiety in the game player.

5.3. Design and Procedure

This study adopted a short-term longitudinal research approach in which each participant was expected to complete two sessions. A longitudinal research design was chosen because it was necessary to collect data from the same sample at two or more different points in time so as to determine how the participants managed and controlled their anxiety levels with the BCI neuro-feedback. It should be noted that a key aspect of a longitudinal design is the time factor. However, time factor is not only measured based on the duration of the study. Researchers (Karapanos, Martens, & Hassenzahl, 2009; Singer & Willett, 2003) have argued that one way of measuring time in a scientific study is to look at it in terms of the number of data gathering waves. This typically looks at how many data gathering waves occur in a single session or across several sessions which could all span in the same day or across several days. Tullis and Albert (2013) adopted a similar view in explicating how learnability can be measured in usability studies. Prior literature and empirical findings suggested that scientific longitudinal studies should have at least three data gathering waves in order to effectively capture change (Karapanos *et al.*, 2009; Karapanos, Zimmermann, Forlizzi, & Martens, 2010; Singer & Willett, 2003). These approaches have been successfully used in many scientific studies. For example, Rieger (2009) demonstrated that change process in a longitudinal study could be sufficiently observed within a 2.5 hour session with several data gathering waves. Combaz *et al.* (2013) used two BCI session with each session lasting between 1-2 hours (if the participant was not tired) in order to evaluate change process with regards to BCI performance and cognitive workload of two spelling BCI applications.

Based on this argument, this study adopted an approach with two sessions per participant that took place on two separate days. Each session had four data gathering waves for math anxiety, with a break (distracter task) after the second data gathering wave. The participants had to play two levels (level one and level five) of the Math-Mind Game. The two levels have different difficulties based on the mathematics problems they present. The game had four key math problems which were addition, subtraction, division and multiplication. During each session, the participants played each of the two levels twice with data captured each time a level was played. Feedback to the participant was provided after the task was completed to see his/her overall level of math anxiety during the task and to provide advice on how to control math anxiety in the next task. A schematic view of the research procedure is presented in Figure 4 below.

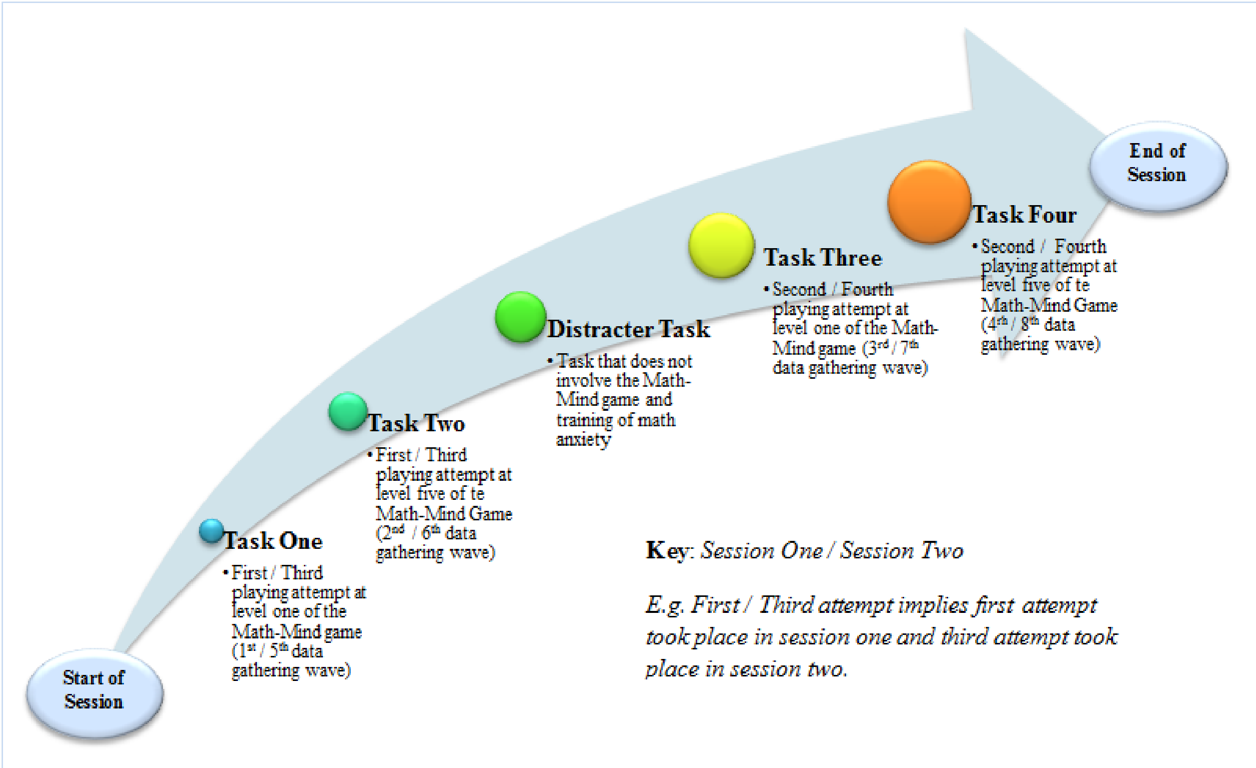


Figure 4: Study design and task sequence for testing sessions one and two

6. Results and Discussion

Out of the 36 participants who took part in the study, only 25 completed the two sessions. However, because four data gathering waves took place during the first session, full data for all participants will be used when analysing data relating to the first session. This is because each session was carried out in a way that allowed for effective capturing of changes in math anxiety. As such, when analysing information that spans across the two sessions, only the data for the 25 participants who completed both sessions will be used. This information will be clearly indicated with each analysis.

6.1.Training math anxiety

The math anxiety findings from the FSMAS are presented in Table 1 below.

Table 1: FSMAS measures and relationship to Age, Gender and Grade

Statements	Descriptive Statistics			Correlation		
	Mean	Std. Dev	Skew- -ness	Age	Gender	Grade
1. Mathematics does not scare me at all.	1.62	0.922	1.13	0.326**	-0.097	0.155

2. It would not bother me at all to take more mathematics courses.	2.74	1.62	0.14	-0.216	0.333**	-0.264
3. I usually do not worry about my ability to solve mathematics problems.	2.24	1.44	0.86	0.327**	-0.166	0.357**
4. I have always been at ease during mathematics tests.	2.41	1.28	0.35	0.586***	-0.233	0.602**
5. Mathematics makes me feel uncomfortable and nervous.	3.91	1.29	-0.82	-0.337**	-0.301	-0.224
6. I always feel tense when I think of trying hard mathematics problems.	3.74	1.26	-0.52	-0.312	-0.260	-0.233
7. My mind goes blank and I am unable to think clearly when working mathematics.	3.85	1.44	-1.09	-0.248	-0.210	-0.221
8. Mathematics makes me feel uneasy and confused.	3.41	1.37	-0.29	-0.060	-0.043	0.018
Overall Math Anxiety Score	**2.26**	**0.93**	**0.504**	**0.327****	**0.092**	**0.251**

*** $p < 0.01$; ** $p < 0.05$

The FSMAS components in Table 1 are composed of both positively worded (1-4) and negatively worded (5-8) questions. In computing the overall math anxiety score, the negatively worded questions are reversed so that a higher score indicates a high level of math anxiety. The overall mean math anxiety score is 2.2 which indicate that the level of math anxiety is moderate among most of the participants in the study. This score is slightly lower than that of previous studies in South Africa (Mutodi & Ngirande, 2014; Hlalele, 2012). However, these studies used a larger sample with most of their participants above 16 years. It is imperative to acknowledge this difference in age groups as prior studies (Woodard, 2004; Balogˇlu & Koçak, 2006; Mutodi & Ngirande, 2014) have indicated a significant relationship between math anxiety and age. This relationship is confirmed in this study by the significant positive correlation between age and overall math anxiety score indicating that math anxiety increases with age. This is probably because older students have been exposed to more difficult mathematics problems than younger students. Contrary to prior studies (Yüksel-Şahin, 2008; Ho *et al.*, 2010; Jain, 2009; Mutodi & Ngirande, 2014; Devine, Fawcett, Szucs & Dowker, 2012) gender and grade did not show a significant relationship with the overall math anxiety score. Nonetheless, the findings are in line with other studies (Dede, 2008; Tapia, 2004; Birgin, Baloğlu, Çatlıoğlu & Gürbüz, 2010) that have also found no significant relationship between math anxiety and gender. However, the correlation results between component 2 of the FSMAS and gender provides significant evidence that female learners are more likely to refrain from taking more maths courses than male learners which is again consistent with prior studies (Yüksel-Şahin, 2008; Devine *et al.*, 2012).

The next step was to examine if the math anxiety measured with the FSMAS was similar to the physiological arousal measure of math anxiety obtained from the BCI device. Similar to Cates and Rhymer (2003), the participants were classified into two groups (high and low math anxiety) based on their overall math anxiety score from the FSMAS. The median math anxiety score for all participants in the study was used as the separation point with participants classified as having low anxiety if they scored at or below the median, and high math anxiety if they scored above the median. Cates and Rhymer (2003) elucidate that this approach of using the median is superior to other approaches because it controls for any artificially inflated differences between groups often observed in methods that classify the groups based on the upper and lower quartile scores. After classifying the participants into high and low math anxiety groups, an independent sample T-test was used to compare the differences in the BCI measured math anxiety for the first time the participants played each of the two game levels. Only the first time for each level was used because it was expected that by the second time a participant plays the same level, he/she has already received feedback on math anxiety from the first time with guidance on how to control anxiety. As such, the math anxiety score from the second gameplay would already have been influenced by prior biofeedback and training using the BCI. The results of the independent sample T-test are depicted in Table 2 below.

Table 2: Comparing FSMAS scores to Math Anxiety scores of the BCI

	Mean Anxiety Values		T-test for equality of means	
	High Math Anxiety Group	Low Math Anxiety Group	T-Value	P-Value
Level One Math Anxiety	58.360	46.706	1.430	0.163
Level Five Math Anxiety	59.193	36.658	2.376	0.024**
Average Math Anxiety	58.777	43.182	2.174	0.037**

** $p < 0.05$

The results in Table 2 indicate that the high math anxiety group from the FSMAS had a higher mean BCI measured math anxiety compared to the low math anxiety group. The results are, however, not significant for level one of the Math-Mind game. This could possible account for the fact that level one math exercises are very easy and so exert a limited amount of math anxiety on most of the participants. Nonetheless, the results for level five of the Math-Mind game and the average for both levels are significant at the 5% level. This clearly depicts that the level of math anxiety measured with the FSMAS is significantly related to that measured with the BCI. This finding support the view of prior studies (Medeiros and Leclercq, 2007; Mattarella-Micke *et al.*, 2011) that math anxiety can be measured in terms of physiological arousal.

Since the results from Table 2 indicate that the captured math anxiety by the BCI is valid, it is imperative now to evaluate if the participants used the neuro-feedback from the BCI to control and reduce their level of math anxiety as the different tasks progressed. A paired sample t-test (Table 3) was used to evaluate differences in the levels of math anxiety for the different tasks.

Table 3: Paired sample T-test for math anxiety across task.

	N	Mean Anxiety Values		T-test for equality of means	
		1st Task	2nd Task	T-Value	P-Value
Panel A: Session One					
Pair One	36	50.792	29.208	4.232	0.000***
Pair Two	36	47.144	29.972	5.160	0.000***
Panel B: Session Two					
		3rd Task	4th Task		
Pair Three	25	35.072	21.967	3.626	0.001***
Pair Four	25	32.368	18.592	4.367	0.000***
Panel C: Comparison across the two Session					
		Session1	Session 2		
Pair Five	25	39.926	28.520	2.377	0.026**
Pair Six	25	42.048	25.480	3.972	0.001***

*** $p < 0.01$; ** $p < 0.05$

Pair one (pair two) indicates the comparison between the two attempts at playing level one (level five) of the Math-Mind game during the first session of the study. The t-test indicates a significant difference in the level of math anxiety for the two attempts indicating that there was a significant reduction in the level of math anxiety for the second attempt for each of the levels was played. This indicates that the feedback on math anxiety that the participant's received from the first task of each level helped them to train how to control math anxiety and effectively reduced it. This in turn shows that math anxiety can be trained within a single session thus supporting the view of Tullis and Albert (2013) that learnability can be measured over a single session with a break in-between the task.

Pair three (pair four) indicates the comparison between the two attempts at playing level one (level five) of the Math-Mind game during the second session of the study. The findings also indicate a significant reduction in the level of math anxiety for the second attempt the game was played in the second session (4^{th} task) compared to the first time (3^{rd} task). These findings align with the findings from the first session and thus support the view that a BCI device can be used to significantly train and reduce math anxiety.

Pair five (pair six) indicates the comparison between the two attempts at playing level one (level five) of the Math-Mind game for each of the two sessions. The findings indicate a significant reduction in math anxiety for the second session compared to the first session. Based on all six comparisons, it can be stated that neuro-feedback from the BCI on real time physiological arousal can be used to train learners in controlling and reducing their level of math anxiety. The findings also support prior studies (Gresham, 2007; Hendel & Davis, 1978; Tooke & Lindstrom, 1998; Karimi and Venkatesan, 2009; Scneider and Nevid, 1993; Sharp *et al.*, 2000) which highlighted that math anxiety can be controlled and reduced. In the next section, a regression analysis is performed to determine if the measured math anxiety was related to mathematics performance

6.2.Relationship between Math Anxiety and Mathematics performance

This section presents the results on the relationship between math anxiety and mathematics performance following a set of linear regression models (Table 4).

Table 4: Relationship between math anxiety and mathematics performance

	Models					
	Model A		Model B		Model C	
Variables	Beta	T-Stats (*P-Value*)	Beta	T-Stats (*P-Value*)	Beta	T-Stats (*P-Value*)
Constant		9.314 (0.000)***		17.874 (0.000)***		2.175 (0.041)
Math Anxiety	-0.328	-2.350 (0.025)**	-0.856	-6.777 (0.000)***	-0.435	-2.029 (0.045)**
Computer Experience	0.522	3.737 (0.000)***	-0.170	-1.347 (0.192)	-0.278	-1.298 (0.208)
Model Parameters						
Total Observations	36		25		25	
R2	0.398		0.068		0.175	
Adjusted R^2	0.359		0.657		0.096	
F-value (sig.)	10.243 (0.000)***		23.051 (0.000)***		2.222 (0.133)	
R^2 Change	0.271		0.027		0.066	
F-Change (sig.)	13.966 (0.001)***		1.814 (0.192)		1.684(0.208)	
Durbin- Watson Stats	1.539		1.342		1.556	

In Model A (Model B), the dependent variable is the overall mathematics score obtained in the first session (second session) while the explanatory variable is the average math anxiety for each of the corresponding sessions. In Model C, the dependent variable is the change in mathematics performance across the two sessions while the explanatory variable for math anxiety is the change in math anxiety across the two sessions. R^2-change and F-change indicate the effect of controlling for possible computer anxiety influenced by a participant's prior computer experience.

*** $p < 0.01$; ** $p < 0.05$

In evaluating the impact of math anxiety on mathematics performance, this study acknowledged the fact that all the participants did not have the same level of computer experience, and as such, some level of anxiety could have been a result of computer anxiety. Existing empirical evidence (Sam, Othman & Nordin, 2005; Dupin-Bryant, 2002; Lee & Huang, 2014; Terujeni, Lavasani, Karamdust & Hassanabadi, 2013) has indicated that prior usage and exposure to computers significantly reduces the levels of computer anxiety. As such, participants who had a low level of computer anxiety could possibly perform better in the game task than those with a high level of computer anxiety. This is because those with high computer anxiety will struggle more using the computer which might also influence the measured physiological arousal. Based on this assumption and the fact that prior computer experience is a proxy for computer anxiety (Dupin-Bryant, 2002; Terujeni *et al.*, 2013), this study used the participants' prior exposure to computers as a control factor to ascertain the influence of math anxiety of mathematics performance.

In Model A (Table 4), it is seen that math anxiety has a significant negative relationship with mathematics performance. This indicates that high maths anxiety results in poor mathematics performance. The findings are consistent with prior studies (Zakaria *et al.*, 2012; Ashcraft & Krause, 2007; Jansen *et al.*, 2013; Ramirez *et al.*, 2013) which also indicated a significant negative relationship between math anxiety and mathematics performance. The significance of the F-change value indicates that controlling for the effect of computer experience is vital as it has a significant influence on the model. The R^2-change (0.271) indicates that computer experience reduces the error of using math anxiety to predict mathematics performance by 27.1%. This shows that for session one a significant level of the anxiety could have been induced by computer experience as participants who had little computer experience had to struggle with the computer in addition to the mathematics exercises. The results also show that the participants with more prior computer experience scored better in the mathematics exercises of the Math-Mind game. This finding aligns with observations during the first session which showed that some of the participants failed to answer the questions on time because they were struggling with the mouse to click the correct answer. As such, they scored comparatively lower due to their computer competence and not their mathematics competence. This further supports the view of controlling for the effect of computer experience when evaluating how the measured math anxiety impacts on mathematics performance.

In model B, math anxiety also has a significant negative relationship with mathematics performance. The math anxiety Beta value in model B is more than double that of model A indicating that math anxiety had a stronger relationship in model B than in model A. The F-change value is insignificant showing that that computer experience did not significantly influence the findings in the second session. It is seen that the variance explained by computer anxiety is only 2.7% compared to 27% in model A. This indicates that by the second session, participants with little computer experience had already learned how to use the computer well in completing the exercises of the Math-Mind game. As such, there is little or no computer induced anxiety that could significantly affect the relationship between math anxiety and mathematic performance. This supports evidence form prior studies (Sam *et al.*, 2005; Dupin-Bryant, 2002; Lee & Huang, 2014; Terujeni *et al.*, 2013) which indicate that exposure to computers reduces computer anxiety.

In Model C, the change in math anxiety between the first and second sessions has a significant negative effect on the change in mathematic performance. This shows that a participant who significantly trained and reduced his level of math anxiety in the second session compared to the first session scored higher in the mathematics exercises and vice versa. Although this relationship is significant at the 5% level, the F-value for the overall model is not significant. So the effect of anxiety change across the two sessions on mathematics performance must be treated with caution.

Nonetheless, these results are expected based on the findings from model A and model B as it is seen that computer induced anxiety affected the measure of math anxiety in session one. As such participants with little computer anxiety could have recorded very high anxiety levels in session one compared to the participants with more computer experience. During the second session, the participants with little computer experience were therefore much likely to have a higher change in the level of math anxiety as their computer experience during the first session had reduced the level of anxiety induced by the computer competence. As such, the magnitude of the change in anxiety could not possibly reflect the exact change in mathematics performance when compared to the participants who had more computer experience prior to the first session. This argument is supported by the negative coefficient (-0.278) of computer experience in model C which indicates that participants with more prior computer experience had a smaller change in mathematics performance across the two sessions, than participants with little or no prior computer experience. This aligns with the findings presented in model A that people with more prior computer experience performed better in the math exercises.

7. Limitations of the Study

Although this study adopted a systematic and well thought-out research design for evaluating the change process (in this case changes in math anxiety) as established by prior studies (Karapanos *et al.,* 2009; Karapanos *et al.,* 2010; Singer & Willett, 2003; Rieger, 2009; Combaz *et al.,* 2013; Tullis & Albert, 2013), it is not without limitations. Firstly, the study adopted a within-subjects design with eight data gathering waves to ascertain changes in the participant's level of math anxiety across two sessions that took place on separate days. However, one cannot state with certainty the actual components of the application that significantly contribute to the reduction in the level of math anxiety. To address this situation going forward, future studies can utilize a control group that does not view the real time level of math anxiety from the BCI as well as visual feedback when the level of math anxiety increases from its current state. Also, a control for the overall level of math anxiety for each task presented at the end of the task can be examined to determine its effect on reducing math anxiety. Since this study was a proof of concept on using a BCI-based solution for training and reducing math anxiety, the general assumption adopted from existing studies (Ávila, Chiviacowsky, Wulf & Lewthwaite, 2012; Chiviacowsky & Wulf, 2007) was that effective feedback will improve the participants learning on how to manage and control math anxiety. In order to improve the effectiveness of using a BCI-based solution for reducing math anxiety, future studies can investigate this association further by using different visual feedbacks and control groups to provide a more detailed insight on the subject.

Secondly, human emotions are a complex thing to study. This is because at a given point in time, several different emotions can be produced by an individual. So by singling out only one emotional component (math anxiety) this study is limited from determining the role other emotional components could play in the training and reducing of math anxiety. For example, researchers (Tractinsky *et al.,* 2000; Wolfson & Case (2000) focusing on multimedia learning platforms have shown that positive emotions are produced from different design aspects like layout, colour, sound etc. As such, such emotions can be produced by the game and thus play an unrecognized role in the results obtained in this study. Recent studies (Garcia-Molina, Tsoneva & Nijholt, 2013; Pell, Monetta, Rothermich, Kotz, Cheang & McDonald, 2014) have also shown significant dependencies between human emotions (affective states) and cognitive functions.

Therefore, controlling for the effect of cognitive functions like working memory and inhibitory control that have been shown to play a significant role in learning mathematics could better ascertain the relationship between math anxiety and mathematic performance and whether these cognitive functions have any influence on the training to reduce math anxiety. Nonetheless, researchers (Lyons & Beilock, 2012) using functional magnetic resonance imaging to examine brain activity have shown that math anxiety can be isolated as an individual emotion and studied.

8. Conclusion

The central aim of this study was to determine if a BCI-based mathematics educational game could be used to reduce math anxiety in students. Math anxiety has been widely acknowledged as a critical factor with a significant negative impact on mathematics performance (Zakaria *et al.,* 2012; Ashcraft and Krause, 2007; Jansen *et al.,* 2013). With most countries around the world suffering from "math crisis" (Schoenfeld, 2005; Pausigere, 2011); it becomes imperative to identify the factors that account for the poor mathematics performance such as math anxiety and find ways of controlling them. Interestingly, prior studies (Gresham, 2007; Hendel & Davis, 1978; Tooke & Lindstrom, 1998; Karimi and Venkatesan, 2009; Scneider and Nevid, 1993; Sharp *et al.*, 2000) have indicated that math anxiety can be trained and reduced. This study adds to the evidence from prior studies by indicating following a repeated measure t-test that math anxiety can be trained and reduced with the aid of a BCI-based mathematics educational game. The results also showed that the level of math anxiety captured with the widely used FSMAS was similar to that captured with the BCI. This is a novel finding as BCI devices have been known to have a great potential for educational purposes, however, little empirical evidence exists to support these arguments. Also, unlike prior cognitive psychological methods of reducing math anxiety that need to be administered by a trained professional, the BCI math-mind game can be used with little or no technical support by the students or their parents/guardians. This thus provides a home based solution for reducing math anxiety especially as the cost of consumer BCI devices have significantly dropped over the years.

The results in this study also indicated a significant negative relationship between math anxiety and mathematics performance. The findings are congruent with other studies that have also shown that high math anxiety results in poor mathematics performance. In addition, it was seen that when using a computer based system to capture math anxiety, it is vital to control for the effect of computer anxiety especially when all the participants do not have the same level of competence in computer usage. This study showed that computer induced anxiety significantly affected mathematics performance during the first session of the study, however by the second session, all the participants where already proficient in using the computer for playing the math-mind game and it was seen that the effect of computer anxiety completely diminished. As such, computer proficiency is therefore a key factor that needs to be controlled in studies that utilize computers for achieving educational goals.

Lastly, this study replicated the findings of prior studies (Woodard, 2004; Balogˇlu & Koçak, 2006; Mutodi & Ngirande, 2014) that established a significant relationship between age and the overall math anxiety of students. Furthermore, this study is congruent with prior studies (Dede, 2008; Tapia, 2004; Birgin *et al.,* 2010) that failed to find a significant relationship between gender and math anxiety, however, the results contradict those of researchers (Yüksel-Şahin, 2008; Ho *et al.,* 2010; Jain, 2009; Mutodi & Ngirande, 2014; Devine *et al.,* 2012) that have argued that math anxiety is significantly related to gender. Nonetheless, this study showed evidence that some components of math anxiety and not the overall math anxiety has a significant relationship with gender. Lastly, future studies could compare the BCI-based intervention for math anxiety with existing methods like the CBGT to determine the most appropriate method for reducing math anxiety in school children.

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