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Validating The Use Of Mobile EEG To Investigate Neural Markers Of Real-World Successful Sporting Performance In Elite Athletes

Georgia Alexandrou

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Declaration

I hereby declare that the content of this thesis is original and has not been submitted in whole or in part for consideration for any other degree or qualification. I also declare that the thesis embodies the results of my own research.

The PhD was funded by SportScotland from 2017-2021, however, the funders did not have any input into the data analysis, interpretation and writing of the thesis. I declare that the research presented here is issued from my own intellectual work and was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The experiments were designed based on the collaborative work with Professor David Donaldson, Dr Malcolm Fairweather and coaches. The study in Chapter 3 was designed in collaboration with Professor David Donaldson and the research team at Foro Italico University in Rome, Professor Francesco Di Russo, Dr Marika Berchicci and Dr Federico Quinzi as part of the Postdoctoral Early Career Researcher Exchange funded by SINAPSE.

To complete time frequency and power spectral density analysis the EEG data was processed through MATLAB using the open-source toolbox of EEGLAB (v13, Delorme & Makeig, 2004). The basis for the pre-processing pipeline and associated scripts were developed by Dr Simon Ladouce and adapted by myself to fit my experimental paradigms.

This thesis adheres to the University of Stirling guidelines for thesis presentation specifying font, 12 font size, 1.5 spacing, margins size (binding edge 35mm and other margins not less than 20mm) and mirror margins to allow for doubled-side printing.

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Scientific Dissemination

Part of this work has been communicated as follows:

Invited Talks

- Understanding mind and performance links in real-world sporting environments – (Conference Symposium, The British Psychological Society, Cognitive Psychology Division, Stirling Scotland, 2020)

- Investigating Differences in neural activity underlying curling performance – (Presentation to Curling Coaches and Sports Professionals organized by SportScotland, Stirling Scotland, 2020)

Abstract

This thesis examines the cognitive and neural processes supporting expert performance in the context of elite sport. We review the existing sports EEG literature, highlighting that it has poor ecological validity. Until recently the findings characterizing sporting performance and expertise have largely arisen from laboratory-based experiments. However, recent technical developments mean that EEG data can now be collected in more ecologically valid field-based settings, during the performance of real sporting behaviour - particularly in target sports where movement is limited. In addition, our literature review led us to identify that most studies investigating sporting expertise performance have employed study designs that compare experts to novices. Although these findings provide insight into the neural mechanisms differentiating experts and novices, they do not necessarily provide information about the neural mechanisms underlying successful and unsuccessful performance within experts. Consequently, the aim of this thesis was to build on the existing literature, investigating the feasibility of recording neural activity in expert athletes in ecologically valid settings, and examining any differences in neural activity relating to successful and unsuccessful sporting performance across a range of sports. Throughout the thesis we assessed neural activity using mobile EEG, employing both group average and N=1 approaches. Time frequency analysis was used to explore the data, providing new understanding of the neuronal changes that occur during performance in expert athletes. Findings demonstrate the feasibility of examining neural activity as a function of performance in ecologically valid settings. The data reveal observable neural signatures that differ as a function of performance levels, that differ between athletes, and that differ across sports. Across the studies presented in this thesis the findings highlight the importance of adopting an individualised approach, and the need to tailor the analysis of EEG data for each athlete. Taken together, the findings provide real-world evidence regarding the neural mechanisms dissociating successful and unsuccessful performance in expert athletes across sports, suggesting that mobile EEG offers exciting new opportunities for understanding and supporting elite sporting performance.

Contents

Chapter 1: General Introduction 1

1.1 Preface 1

1.2 Rationale for a real-world approach in a sporting context 3

1.3 Ecological validity and the need for a mobile cognition approach in sports 4

1.4 Rationale for investigating neural mechanisms underlying sporting behaviour 9

1.4.1 Alpha Frequency in the Sporting domain 17

1.5 Emergence and current challenges of mobile EEG technique 32

1.6 Conclusion 34

Chapter 2: Recording, processing and analysing real-world EEG dynamics within a sporting context. 36

2.1 Methodological challenges of mobile EEG 36

2.1.1 Acquisition of event-related brain activity in real-world context.. 38

2.1.2 Movement artifacts during natural sporting behaviour 40

2.2 Acquisition procedure of ecological valid EEG data 40

2.2.1 Recording Equipment Characteristics 41

2.2.2 Processing Pipeline for mobile EEG data 41

2.3 Data Analysis 50

2.4 Baseline correction 51

2.5 Statistical Analyses 54

2.6 Final Considerations 55

Chapter 3: Exploring the neural dynamics underlying performance during pistol shooting in a real-world shooting range. 56

3.1 Introduction 56

3.2 Shooting studies 57

3.2.1 Alpha Frequency (8-12 Hz) 57
3.2.2 Theta Frequency (4-7 Hz) 65
3.2.3 Sensorimotor Rhythm (13-15 Hz) and Beta Frequency (15-30 Hz) 67
3.3 Issues arising in shooting: EEG methods and rationale for present study 69
3.4 Methods 72
3.4.1 Participants 72
3.4.2 Experimental Design 72
3.4.3 Material 73
3.5 Procedure 73
3.6 Data Processing 74
3.7 Data Analyses 77
3.8 Results 78
3.8.1 Behavioural Performance 78
3.8.2 Time-Frequency analysis 79
3.8.3 Additional Targeted analysis 90
3.8.4 Root Mean Square (RMS) 99
3.9 Discussion 102
Chapter 4: Identification of Individual Alpha Peak Frequency and the exploration of the neural dynamics characterizing successful and unsuccessful performance between two elite athletes. 112
4.1 Introduction 112
4.2 Individual Alpha Peak Frequency 113
4.3 Small number studies 117
4.4 Rationale for exploring neural power in two elite athletes. 122
4.5 Methods 124
4.5.1 Participants 124

4.5.2 Experimental design 124

4.5.3 Material 126

4.5.4 Procedure 127

4.5.5 Data Processing 128

4.6 Results 133

Shooting Behavioural performance 134

4.6.1 EEG Analysis 138

4.7 Discussion 177

Chapter 5: Investigating neural activity in a real-world curling task 188

5.1 General Introduction 188

5.2 Introduction to Curling 189

5.3 Methods 196

5.3.1 Participants 196

5.3.2 Experimental design 197

5.3.3 Material 198

5.3.4 Procedure 199

5.3.5 Data Processing 200

5.4 Results 203

5.4.1 Curling Behavioural Performance 203

5.4.2 EEG Analysis 210

5.4.3 Time-Frequency Analysis 210

5.4.4 Alpha (8-12 Hz) 211

5.4.5 Low Alpha (8-10 Hz) 216

5.4.6 High Alpha (10-12 Hz) 218

5.4.7 Theta Activity (4-7 Hz) 221

5.4.8 Beta Activity (15-30 Hz) 222

5.4.9 SMR Frequency (13-15 Hz) 223

5.4.10 Root Mean Square (RMS) 224

5.5 Discussion 226

Chapter 6: General Discussion…………………………………………...234

6.1 Summary of Findings………………………………………………234

6.2 Concluding Remarks………………………………………………...251

Appendix A……………………………………………………………….254

References……………………………………………………………….256

List of Figures

Figure 1.1. Example of fully portable EEG system…………………………...8
Figure 2.1. ICA of eye blinks related artifacts………………………………44
Figure 2.2. ICA of lateral eye movement related artifacts…………………....45
Figure 2.3. Raw EEG data prior to any data transformation……………….46
Figure 2.4. Raw EEG data after ICA and SASICA transformation………..46
Figure 2.5. Identified SASICA components for rejection…………………..47
Figure 3.1. Behavioural shooting performance of participants…...……......78
Figure 3.2. Frontal time-frequency plot of shooting performance…………80
Figure 3.3. Central time-frequency plots of shooting performance………..81
Figure 3.4. Parietal time-frequency plots of shooting performance……….82
Figure 3.5. Occipital time-frequency plots of shooting performance……..83
Figure 3.6. Shooting performance alpha scalp maps……………………...84
Figure 3.7. Change of alpha activity over time………………………………86
Figure 3.8. Shooting performance theta scalp maps…………………….....87
Figure 3.9. Shooting performance beta scalp maps………………………..88
Figure 3.10. Shooting performance SMR scalp maps……..……………….89
Figure 3.11. Alpha parietal time-frequency plots……………………………91
Figure 3.12. Alpha scalp maps -1000ms to 0 shooting performance….......92
Figure 3.13. Difference time-frequency plot shooting performance……....94
Figure 3.14. Theta scalp maps -500ms to 0 shooting performance……….96
Figure 3.15. Central time-frequency plot beta activity……………………...97
Figure 3.16. SMR scalp map -1000ms to 0 shooting performance……....98
Figure 3.17. Root mean square frontal baseline period.…………………100
Figure 3.18. Root mean square central baseline period.………………...101
Figure 3.19. Root mean square parietal baseline period…….…………..101
Figure 4.1. Mobile EEG setup in real world shooting task……………....125
Figure 4.2. Total trials of shooting performance in time range bins P1…130
Figure 4.3. Total trials of shooting performance in time range bins P2….131
Figure 4.4. Relationship between shooting performance and 10a0 P1…136
Figure 4.5. Relationship between shooting performance and breach P1.136
Figure 4.6. Relationship between shooting performance and breach P2.137
Figure 4.7. Root Mean Square baseline period P1……….……………139

Figure 4.8. Root Mean Square baseline period P2……………………………139
Figure 4.9. Time frequency plot frontal region P1……………………………..140
Figure 4.10. Time frequency plot central region P1………………………….141
Figure 4.11. Time frequency plot parietal region P1…………………………..142
Figure 4.12. Time frequency plot occipital region P1………………………..143
Figure 4.13. Alpha scalp maps P1……………………………………………144
Figure 4.14. Mean alpha and Confidence Intervals P1………………………..145
Figure 4.15. Low alpha scalp maps P1…………………………………………146
Figure 4.16. Low alpha activity and Confidence Intervals P1……………146
Figure 4.17. High alpha scalp maps P1………………………………………..147
Figure 4.18. High alpha mean activity and Confidence Intervals P1…….148
Figure 4.19. Targeted analysis alpha and Confidence Intervals P1……149
Figure 4.20. Individual Alpha Peak scalp maps P1…………………………..150
Figure 4.21. Individual Alpha activity and Confidence Intervals P1…….151
Figure 4.22. Low Individual Alpha Peak scalp maps Participant 1……….151
Figure 4.23. Low Individual Alpha activity and Confidence Intervals P1..152
Figure 4.24. High Individual Alpha Peak scalp maps Participant 1……..153
Figure 4.25. High Individual Alpha activity and Confidence Intervals P1.154
Figure 4.26. Individual Alpha Peak Targeted analysis P1 ………………155
Figure 4.27. Theta scalp maps P1……………………………………………156
Figure 4.28. Theta mean activity and Confidence Intervals P1…………157
Figure 4.29. Individual theta scalp maps P1…………………………………157
Figure 4.30. Individual theta mean activity and Confidence Intervals P1.158
Figure 4.31. Beta scalp maps P1……………………………………………159
Figure 4.32. Beta mean activity and Confidence Intervals P1…………..160
Figure 4.33. SMR scalp maps P1…………………………………………….160
Figure 4.34. SMR mean activity and Confidence Intervals P1…………..161
Figure 4.35. Time frequency plot frontal region P2…………………………162
Figure 4.36. Time frequency plot central region P2…………………………163
Figure 4.37. Time frequency plot parietal region P2…………………………..164
Figure 4.38. Time frequency plot occipital region P2………………………..165
Figure 4.39. Alpha scalp maps P2……………………………………………166
Figure 4.40. Mean alpha activity and Confidence Intervals P2………....167
Figure 4.41. Low alpha scalp maps P2………………………………………168

Figure 4.42. Mean low alpha activity and Confidence Intervals P2……..168
Figure 4.43. High alpha scalp maps P2……………………………………...169
Figure 4.44. Mean high alpha activity and Confidence Intervals P2……169
Figure 4.45. Targeted analysis alpha activity P2…………………………171
Figure 4.46. Theta scalp maps P2…………………………………………....172
Figure 4.47. Mean theta activity and Confidence Intervals P2…………..173
Figure 4.48. Targeted analysis theta activity P2……………………..…...174
Figure 4.49. Beta scalp maps P2……………..……………………………174
Figure 4.50. Beta mean activity and Confidence Intervals P2………......175
Figure 4.51. SMR scalp maps P2…………………………………………176
Figure 4.52. SMR mean activity and Confidence Intervals P2………......177
Figure 5.1. Example of curling game………………………………….……190
Figure 5.2. Target area for purposes of curling task ……………………199
Figure 5.3. Successful stone delivery rate (%) across blocks…………...204
Figure 5.4. Successful stone delivery rate (%) for each participant…….205
Figure 5.5. Distribution of stone location for all participants…………….206
Figure 5.6. Distribution of stone location for participant 7……………….209
Figure 5.7. Alpha scalp maps………………………………………...….211
Figure 5.8.CP5 electrode time-frequency plot ……………………………213
Figure 5.9. C4 electrode time-frequency plot …………………………… 214
Figure 5.10. Low alpha scalp maps…………………………………...…...216
Figure 5.11. High alpha scalp maps………………………………...……218
Figure 5.12. Theta scalp maps……………………………………….........220
Figure 5.13. Beta scalp maps……………………………………...…...…222
Figure 5.14. SMR scalp maps………………………………………...…...223
Figure 5.15. Root Mean Square at F4/FC6 electrode……………………225
Figure 5.16. Root Mean Square at C4 electrode……………………..…225
Figure 5.17. Root Mean Square at CP5 electrode……………………..…225
Figure A.1. Relationship between shooting performance and alpha activity P1…………………………………………………………………………...254
Figure A.2. Relationship between shooting performance and theta activity P2…………………………………………………………………………...255

List of Tables

Table 1.1. Overview of sport studies and psychological interpretation……11
Table 3.1. Overview of differences across sport EEG studies…………….63
Table 3.2. Independent Components rejected after SASICA……………..76
Table 3.3. Descriptive statistics of shooting performance………………….79
Table 3.4. Total successful and unsuccessful EEG trials………………….79
Table 4.1. Independent Components removed (Chapter 4)……………..129
Table 4.2. Descriptive statistics of shooting performance (P1)…………134
Table 4.3. Descriptive statistics of shooting performance (P2)…………134
Table 4.4. Shooting performance for both athletes………..………………135
Table 4.5. Correlational analysis for Participant 1…………………………135
Table 4.6. Correlational analysis for Participant 2…………………………137
Table 5.1. Independent Components removed (Chapter 5)……………..200
Table 5.2. Average time pushing out of the hack……………….…………201
Table 5.3. Descriptive statistics of curling performance……..……..…..205
Table 5.4. Properties of circular statistics for curling performance……...208
Table 6.1. Overview of EEG changes across PhD………………………..236

Chapter 1: General Introduction

This introductory chapter will focus on the rationale for investigating cognition and behaviour in a real-world sporting context. A review of studies undertaken around sports and EEG will be presented and discussed, outlining the limitations of previous research, and highlighting the need for more exploration. The rationale for the studies developed during this PhD will be introduced in this chapter, within the context of the mobile cognition approach.

1.1 Preface

There is a growing body of evidence revealing differences in brain activity underlying sporting behaviour in experts versus novices, and during successful versus unsuccessful sporting performance. Until recently, the use of laboratory-based experiments in which the environment and stimuli are artificial, and responses from participants are fixed, has resulted in findings that are far from being task representative, a notion introduced by Brusnwik (1956). Technology has advanced, however, resulting in new mobile methods being available (ranging from mobile eye-trackers and pulse meters to mobile force sensors and EMG) that allow traditionally lab-based measurements to be collected in more ecologically valid field-based experiments. The importance of using these novel techniques (in particular mobile EEG) to capture data in a real-world environment will be outlined in the current chapter. The review will also highlight current understanding of the cognitive processes underlying sporting behaviour. In short, the development of novel mobile techniques offers greater ecological validity, and the opportunity of examining interactions between cognition and sporting behaviour in real-world environments.

The work presented in this PhD stems from a wider project: ‘’EEG and Innovation in Sports Performance’’ which was a collaboration between the University of Stirling and Sport Scotland. The project led to the publication of a review article in a high-ranking neuroscience journal stimulating research in the area (Park et al.,2015). This PhD is an extension and development to the project and was designed to answer the stakeholder's (Sport Scotland) question: '' What are the neural processes characterizing successful and unsuccessful performance in elite athletes in real-world settings?'' ''Are there consistent neural signatures characterizing sporting performance across target sport such as Air-Rifle, Pistol shooting and curling?''. The research designs were designed in collaboration with sports professionals (coaches, sport consultants) and athletes to produce an understanding of the existence of any biomarkers supporting sporting performance situated in a real-world environment.

The findings arising from the work performed for this PhD would have significant applied implications for sports professionals and athletes. The pattern of findings from this work from an EEG perspective would provide the basis for future research in the neurofeedback area that can be used to help athletes achieve high levels of performance. The work presented in this PhD provided useful information for the sports professionals and athletes from a behavioural aspect, independently from the EEG. For example, as will be discussed in Chapter 4, although coaches and athletes place a lot of significance in training sessions on the SCATT shooting software system to support athletes' performance, our behavioural results and work has informed sport practitioners to take into account the average score of each individual athlete and investigate performance on an individualistic level. Our findings support the view that the relationship between shooting performance and the SCATT variables do not always correlate, and they differ from individual to individual.

Additionally, the behavioural work from this PhD has provided additional insights and has provided a deeper understanding on how sport professionals, coaches and athletes can investigate curling behavioural performance. As will be discussed in Chapter 5, we applied circular statistics to explore curling performance. We believe that the use of circular statistics will benefit coaches and sports practitioners and will assist them in furthering their understanding of the behavioural profiles of curling athletes.

1.2 Rationale for a real-world approach in a sporting context

The traditional approach to understanding human cognition, and specifically in this case, human cognition in a sporting context, has been to collect data during experiments that take place in simulated (i.e., laboratory) settings.

The dominant approach employed during the collection of such data is to have participants sit still while instructions are given to them, and they are then required to attend to artificial stimuli, making restricted experimentally defined responses. For example, participants might watch a series of flashing lights and make button presses to a specific colour or watch a video of sporting behaviour and rate the skill levels of the performers. A key benefit of the traditional approach of collecting EEG data within a laboratory setting in the general neuroscience domain is that it allows for high levels of experimental control, as the experimenter can manipulate variables (such as counterbalancing the hand used to make responses) and also restrict movement (allowing for better quality data capture).

However, the reality of sporting behaviour is a lot more complex. During sport the human brain needs to adapt, perceive, understand, and act within a changing and complex environment. Thus, by simulating experiments and constraining participants in a laboratory setting, research loses many of the features of real-world sport. As an alternative to the traditional approach, here in the General Introduction we will discuss a new framework, known as Mobile Cognition, that encourages experimental work to be situated in real-world sporting contexts. The mobile cognition approach provides a stepping-stone to advancing research, moving from laboratory settings to real-world contexts. Below, we will review the existing literature on sporting behaviour and expertise, highlighting factors that motivated the development of the mobile cognition framework (Park, Fairweather &

Donaldson, 2015) employed in this thesis.

1.3 Ecological validity and the need for a mobile cognition approach in sports

In 1976, Neisser reported that if we measure human cognition in laboratory settings, the results will advance our knowledge for those specific circumstances but will not necessarily generalize to real-world environments. Asking participants, in a laboratory setting, to look at artificial stimuli on a screen, and make fixed responses, does not capture the demands of behaviour in real-world environments. To address this problem, a central tenet of the mobile cognition approach is that researchers should investigate human cognition in more representative, naturalistic, environments. In the context of sporting behaviour, the mobile cognition approach advocates measuring behaviour during real sporting activity.

Pinder *et al.* (2011) suggested that when designing a practice tasks emphasis should be given towards the need for the athletes to explore their performance environment, as they would in a competitive setting. Representative tasks should be designed so that skill acquisition and performance enhancement in sport can be generalized (Pinder *et al.*, 2011).

A significant aspect of current sport psychology points towards the development of a relationship between theoretical concepts and practical applications. Ecological validity reflects the extent to which research findings in the laboratory can be generalised to the real world (Schmuckler, 2010). In 1943, Brunswik and Lewin had a debate about the environmental context of research and the impact a setting has on a study. A major concern for Brunswik was that psychology was studying ‘’narrow-spanning problems of artificially isolated proximal or peripheral technicalities of mediation which are not representative of larger patterns of life’’ (Brunswik, 1943, p.262).

Representative design is a concept proposed by Egon Brunswik (1956), suggesting that practice tasks should represent the competitive performance environments, so that the learner can maintain the same perceptual-motor relations with key individuals, objects and events (Pinder, Davis, Renshaw & Araujo, 2011). By limiting the design of the task by removing important information sources that athletes rely on and use to perform their actions, different patterns of movement coordination appear (Pinder, Renshaw & Davids, 2009).

The concept of ‘’representative design’’’ , historically, has been proposed by Egon Brusnwik (1956). The idea underlying the term of a representative design was the examination of psychological processes at the level of organism-environment and their relations. Historically, experimental research designs within the sporting domain have been highly controlled and systematic in nature (Dhami et al., 2004). The generalization of such research findings arising from a specific sample to a larger population group had been referred to as external validity (Bracht & Glass, 1968). However, over the years concerns had arisen within the area of sport psychology regarding external validity. Studies of expert performance would be oversimplified and tended to examine behaviours of participants such as skilled University students to study expertise, rather than elite or Olympic athletes (Pinder et al., 2011).

Referring to Egon Brusnwik, who had proposed that *‘’proper sampling of situations and problems may in the end be more important than proper sampling of subjects’’* (Brunswik, 1956, p.39) and this ecological approach of studying cognition assumes that performer-environment interactions are complex situations that rely on picking up information from various sources from the environment (Pinder et al., 2011). In line with Brusnwik’s advocacy for the need of studying performer-environment interactions, sports psychologists have emphasized the need for and importance of ensuring that the experimental designs and constraints represent the task constraints of performance in the training or learning environment (Pinder et al., 2011).

In such representative designs, reflecting real world environments there is a strong emphasis on the relationship between the individual and the environments and this notion is often neglected in general and sport specific traditional EEG and behavioural approaches within the psychological sciences (Dunwoody, 2006). In the sporting domain, athletes use information from the environment (e.g. in curling, the ice friction) to inform their actions (Le Runigo, Benguigui & Bardy, 2005). Drugowitch and Pouget (2010), have suggested that many previous studies in the sporting domain, specifically neuroscience, have failed to implement such representative task designs.

One promising approach to understanding skilled performance in a representative sporting context is to study electrical brain activity using EEG in real-world settings by adopting the mobile cognition approach. As with studies of cognition in general, a major constraint on the traditional use of EEG is that most studies of sporting behaviour were undertaken in the laboratory (which was necessary to allow the recording of EEG), raising the issue of ecological validity. Indeed, to date, there have been a limited number of studies using EEG during real sporting activity. According to Park, Fairweather and Donaldson (2015) the findings from cognition neuroscience research undertaken on sport has not had a major impact on professionals, at least in part because of this lack of ecological validity and task representativeness. The authors report that there is a mismatch between the behaviours measured in laboratory settings and behaviours required in real sporting contexts. Thus, the development of new technology that allows EEG to be mobile and used outside of the laboratory addresses a major constraint for researchers interested in examining sporting behaviours, offering the possibility of new insight into the cognitive and neural basis of real sporting behaviour.

Competition-level athletes are supported by all kinds of professionals (e.g., coaches, physiotherapists, psychologists, etc), with the aim of implementing changes in behaviour (e.g., training routines, responses to fatigue and injury, etc) that will have an impact on winning or losing. Thus, from an applied perspective, sports neuroscience offers an exciting new pathway for understanding the basic mechanisms that underlie sporting behaviour. In this context, understanding the multi-dimensionality of the links between brain activity and sporting behaviour should ultimately lead to enhanced performance. This PhD therefore aims to examine the use of mobile EEG during real sporting activity, extending beyond previous laboratory findings, to further our understanding of the viability of using EEG to measure real-world and inform practice within sports. As Crews and Landers (1993) acknowledge, because EEG has high temporal resolution (revealing dynamic changes in brain activity with millisecond resolution) and because it is relatively cheap, lightweight and easy to use, EEG is highly suited to investigating the neural mechanisms underlying sporting performance.

A good illustration of the compromises required in traditional studies is provided by the work of Babiloni *et al.* (2008), who examined EEG during golf putting to investigate the differences between alpha activity in successful and unsuccessful putts. In their study, expert golfers executed 100 putts on a golf green simulator – a large number of repetitions was required to ensure good signal-to-noise properties within the EEG (a methodological issue we further discuss in Chapter 2). However, because of the constraints around EEG data collection and trial numbers, the researchers adjusted the diameter of the hole for each participant to ensure that 30% of the putts were unsuccessful (108 mm standard, 60-80 mm, adjustable). As predicted, Babiloni and colleagues did report changes in alpha activity related to performance, however, from the perspective of sport professionals the lack of ecological validity was a major concern. Adjusting the size of the hole resulted in a more controlled experimental environment, but at the cost of reduced ecological validity and an unrepresentative task, reducing the relevance of the results to real-world golf behaviour.

Given the concerns that have been raised regarding ecological validity and the need for real-world testing when studying sporting behaviour, the current thesis adopts a mobile cognition approach. Clearly, studying cognition in real-world environments requires technical and methodological innovation, such as the development of portable devices that can operate in the field (see Figure 1.1, Ant-Neuro, Netherlands).

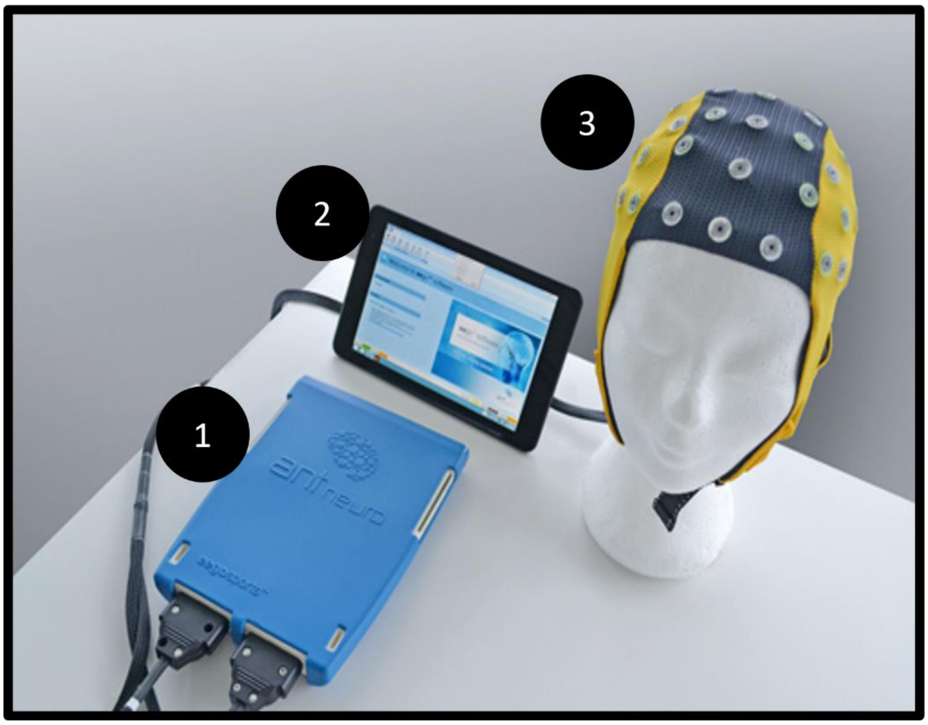


Figure 1.1. An example of a fully portable EEG system: [1] Lightweight and portable amplifier, [2] Lightweight and portable data storage unit, [3] EEG sensors.

Over the last ten years there has been rapid technology development within the field of cognitive neuroscience, leading to advancements in the portability of brain imaging techniques (e.g., development of mobile fNIRs devices, see Gramann, Jung, Ferris, Lin & Makeig, 2014). EEG was previously restricted to use in laboratory settings due to the size, weight and power requirements of the amplifiers, stimulus display computers, etc. However, those limitations can now be overcome with new lightweight, battery powered, portable mobile EEG systems.

Although the development of mobile techniques offers new opportunities in many areas of research, it is perhaps worth highlighting just how important the development is in the context of sport. It is crucial to keep in mind that when testing athletes (to understand the neural mechanisms underlying their sporting performance), the procedures employed should not disrupt their normal sporting behaviour or interrupt their training routines. Put simply, whilst the issue of ecological validity is of primary concern from a scientific perspective, the development of techniques that can be used in an ecologically valid way also means that testing is more viable in elite (i.e., high performance) sports. The number of elite athletes is inherently limited, and the athletes' willingness to engage in research is dramatically reduced if the research interferes in any way with their day-to-day practice.

Traditional laboratory studies addressed this concern by testing athletes in artificial contexts (e.g., by using go/no-go tests to assess differences in attention between novice and elite athletes, see Bekker *et al.*, 2005). By contrast, in principle, the mobile cognition approach allows testing to be carried out during routine practice. Although we highlight how important the issue of ecological validity is, the claim is not that mobile cognition methods can or should entirely replace laboratory-based research, simply that both approaches should be used alongside each other. As noted above, concerns about ecological validity have been raised since 1976, when Neisser argued that examining cognitive processes in artificial environments will advance our understanding in those specific circumstances and not necessarily generalize to the real-world (Neisser, 1976). Our view is that the mobile cognition approach adds to existing laboratory work, especially in real-world sporting contexts, where many of the research questions associated with sporting performance require behaviour to be examined in a naturalistic sporting environment.

1.4 Rationale for investigating neural mechanisms underlying sporting behaviour

As noted above, traditional EEG research in sporting contexts is limited and the existing research raises a range of methodological concerns (e.g., from the removal of artifacts and control over confounds, to issues around reliability and validity). Nonetheless, this chapter will provide an overview of the literature investigating sporting behaviour using EEG, highlighting relevant issues of concern within the previous literature, and outlining how this PhD aims to establish a link between sports and neuroscience. Our current understanding of the neuronal processes within a sporting context remains problematic as there is an absence of standardized methodologies used within the sporting domains and EEG and an absence of consensus regarding the physiological significance of the different frequencies recorded within the sporting domain (Cheron et al., 2016). This might have implications regarding the interpretation of our data, however, we intent to try and understand the different frequencies supporting sporting performance not in isolation as performed in previous sporting studies but how these processes might act together to support sporting performance. We start, however, by introducing a table (Table 1) summarising the findings across sports studies examining power band changes and listing their psychological interpretations. We then move on to further discuss the studies that have been summarised in Table 1 by discussing the neural efficiency hypothesis, the alpha, theta, beta and SMR frequency in the sporting domain. We sum up by introducing an overview of studies using neurofeedback in the sporting domain. Although, neurofeedback has not been employed as a technique within the purpose of this PhD our studies would provide the basis for future research using neurofeedback in the sporting domain to improve sporting performance.

Study	Task/Participant	Epoch/Electrodes	Unit of measurement	Psychological Interpretation
Haufler *et al.,* 2000	Simulation shooting, visuospatial and verbal task Experts: 15 expert National and International level shooters Novices: 21 volunteers with no experience	-6 seconds before trigger pull to 0 (i.e. trigger pull) F3,F4,C3,C4,T3,T4,P3,P4,O1 and O2.	Increase of Alpha (10-11Hz) left central, temporal, and parietal region	Less cortical activation in expert marksmen during the aiming period; fewer cortical resources to process information required to successfully aim the gun on the target compared to novices. Experts characterized as 'automatic performers' who do not rely on verbal- analytic stage and inhibit irrelevant neural processes while other task-relevant neural resources are actively engaged.
			Higher Theta (6-7Hz) in both hemispheres at all sites during the aiming period.	Indicative of sustained attention; experts are intensely engaged with the task demands whilst economically allocating their cortical resources .
Hillman *et al.,* 2000	Simulation shooting Experts: 7 skilled marksmen	-4 seconds to 0 (i.e. trigger pull) F3,F4,C3,C4,T3,T4,P3,P4.	Increased alpha power for rejected compared with executed shots across both hemispheres.	The results are indicative of more effortful processing during rejected shots compared to executed shots.
			Increase of alpha power in the left compared to the right hemisphere for both executed and rejected shots.	Suggesting some degree of specialization and a state of increased processing efficiency; increase of alpha power in the left hemisphere indicates a reduction of verbal processing.

Kerrick ***et al.,* 2001**	Air rifle shooting Experts: 8 skilled marksmen	-8 seconds to 0 (i.e., trigger pull) C3,C4,T3,T4	Increase alpha power (11-13 Hz) in left hemisphere	Suggested to be related to verbal suppression and/or sensorimotor processing. The inhibition of task-irrelevant processes would result to reducing the interference with task-relevant sensory motor processing and provides a basis for the verbal-suppression.
Loze ***et al.,* 2001**	Pistol shooting Experts: 10 experts shooters Less skilled: 9 less skilled shooters	-6 seconds to 0 (i.e., trigger pull) T3,T4, Oz	Increase of alpha power at occipital area prior to best shots and decreased prior to worst shots. Greater alpha power on the left (T3) than on the right (T4) for best shots compared to worst shots.	Shooters reduce their attention to external visual stimuli (aim of pistol or sight) during the pre-shot period of best shots, whereas they increase their attention before worst shots. This suggests that expert shooters are able to shoot successfully without paying maximal visual attention on a target, due to the fact that their motor expertise is built upon autonomous motor control mechanisms, which allow us them to excel in their sport in a cognitively efficient and motorically effortless manner. Indicative of a reduction in verbal-analytical processes, such as ‘’self-talk’’.
Babiloni et al., 2008	Golf Experts: 12 expert golfers	-1 second to 0 (i.e., putt) Fz, FCz, C3, Cz,C4	Higher ERD amplitude for alpha(10-12Hz) prior to successful putts compared to unsuccessful at Fz and Cz and C4 electrodes.	The results suggest fine motor control of movement characterizing successful putts. Additionally, the increased activation of the right hemisphere before successful putts was suggestive of fine control of the left arm and hand movements, which is crucial for successful golf performance.
Doppelmayr et al., 2008	Shooting	-3 seconds to 0 (i.e., trigger pull)	Increase of frontal midline theta (Fz) starting around	Indicative of ability in experts being better in allocating cortical resources during the pre-shot

	Experts: 8 expert shooters Nocices: 10 novice shooters	Fz	2seconds prior to the shot for experts compared to novices where theta activity increases 2.5s prior to shot and then decreases.	period. Novices focus their attention to the target some time before the shot, whereas experts are able to focus their attention correctly to the moment of the shot. Increased theta power over frontal midline areas in experts may be due to some type of controlled, top-down initiated focused attention.
Del Percio *et al.,* 2009	Shooting Experts: 18 pistol shooters Novices: 10 novice shooters	-3 seconds to 0 (i.e., trigger pull) F3,F4,C3,C4,P3,P4,O1,O2.	Experts exhibited global alpha ERD during the pre-shot period compared to novices. Low-alpha ERD(8-10Hz) and high-alpha ERD (10-12Hz) across whole scalp was lower in elite athletes compared to novices. High alpha ERS (10-12Hz) greater amplitude for high performance than low performance at P4 and C3 electrodes for expert shooters.	The authors suggested that elite athletes reach optimal visuo-motor performances, associated with lower cortical activation compared to experts. Index of spatially selective cortical activation suggesting that preparation of visuo-motor performance is related to a smaller decrease of alpha power in elite athletes compared to novices. Low alpha oscillations reflect a person ’s global attentive readiness, whereas high-alpha oscillations reflect task-related sensorimotor and semantic information processing. This would suggest that compared to novices, elite shooters require a selective engagement of cognitive processes and areas that support optimal performance. The results are in line with the neural efficiency hypothesis. The increase of high alpha power over right parietal regions is related to visuo-spatial information processing and spatial attention towards visual targets. Additionally, the increase of high alpha power over the left central region is indicative of sensorimotor

				control of the right hand underlying successful performance.
Kao et al., 2013	Golf Experts: 18 skilled golfers	-3 seconds to 0 (i.e., putt) Fz,Cz,Pz,Oz.	Lower levels of frontal midline theta underlying best putts compared to worst putts.	The data suggest that lower investment in sustaining attention is engaged when expert golfers perform well. Theta activity was observed for both best and worst shots, suggesting that frontal midline theta prior to the backswing is a basic component of expert golfing performance and represents the successful engagement of sustained attention. However, higher levels of frontal midline that in skilled golfer reflects excessive amount of attentional engagements which would damage the successful execution of the automatic performance.
Chuang et al., 2013	Basketball 19 college basketball players	-2 seconds to 0 (i.e., release of basketball) F3,Fz,F4,P3,Pz,P4.	Low (4-6H) and high(6-8Hz) frontal midline theta for successful performance in the preparatory period of a free throw task compared to unsuccessful performance which displayed unstable patterns of high and low frontal midline theta.	Low frontal midline theta (4-6Hz) indicates a more stable arousal state for successful throws. High frontal midline theta (6-8Hz) indicates stability of attentional resources underlying successful throws.
Comani *et al.,* 2014	Air pistol shooting Experts: 3 elite air pistol shooters	-3 seconds to 0(i.e., trigger pull) Prefrontal, frontal, central, parietal & occipital region.	Type 1 and Type 4 performance (optimal-automatic and suboptimal-automatic) were characterized by high alpha decrease prior to the shot at central, left	Lower cortical activation is associated with automatic performance associated with task relevant focus of attention, movement automaticity and fluidity.

			parietal and occipital areas.	
			Increase of high alpha power for type 2 performance (optimal-controlled) in the central areas prior to the shot and in the frontal and occipital areas.	Athletes can successfully perform, without being in an automatic state but by focusing on the core components of the action. Conscious focused attention.
Di Fronso *et al.,* 2016	Shooting 1 air-pistol shooter	-3 seconds to 0(i.e., trigger pull) 32 electrodes;10-20 montage.	Type 3 (suboptimal-controlled) performance characterized by increase in theta ERD in the left temporal area and frontal midline theta.	Increase of theta ERD in left temporal area associated with verbal analytical processes and frontal midline theta associated with controlled attentional engagement. The patterns of results identified suggest decrease of automaticity in movement control.
			Type 1(optimal-automatic) and Type 4 (suboptimal-automatic) performances found to be associated with ERS in low alpha band (8-10HZ).	The pattern of results would suggest automaticity, fluidity and quiescence associated with relaxation states.
			Type 1(optimal-automatic) and Type 4 (suboptimal-automatic) performances found to be associated with ERS in the theta band.	Pattern of results related to a ‘’default mode’’ of autonomous skills and goal-relevant attentional focus during the pre-shot period.

	Type 2 (optimal-controlled) performance associated with decrease of alpha and beta power.	The findings suggest that expert shooters are able to reach successful performances when consciously redirecting their attention to the core components of the action. The finding suggests that focusing attention on important components of the action improves performance, however, directing attention to the execution of automated states will negatively impact performance.

Table 1.1 The table provides an overview of studies within the sporting domain providing a review of their findings and psychological interpretations.

1.4.1 Alpha Frequency in the sporting domain

Alpha rhythms have been suggested to play a role in cognitive processing. In broad terms (e.g., see Klimesch, Sauseng & Hanslmayr, 2007), alpha oscillations are now considered to reflect the inhibition of unnecessary processing of information in the cortex. As reviewed in Table 1.1, sports studies using EEG have largely focused on neural oscillations within the frequency range of 8-12Hz, commonly known as the ‘alpha rhythm’. The alpha rhythm is the most dominant rhythm in the human brain and has been extensively researched, not just in sports, but also in the wider cognitive literature (Basar & Guntekin, 2013). Alpha rhythms were discovered by Hans Berger (1929) and initially associated with disengagement from cognitive processing, but research has gradually confirmed that the alpha rhythm also plays an active role in cognitive processing (e.g., see Klimesch, Sauseng & Hanslmayr, 2007).

From a sport context perspective, the results have been inconsistent on whether alpha increases or decreases are related to successful sporting performance (Babiloni et al., 2008; Baumesiter et al., 2008; Cooke et al., 2014). Although, it is clear that changes in alpha are related to sporting performance, especially in experts, the inconsistent findings might be due to the type of sport investigated (golf, shooting), the use of non-representative task designs (e.g., Babiloni et al., 2008; changing the size of the hole), inconsistency in the selection of electrodes of interest, choice of analysis and baseline. The next sections focus on discussing findings across studies in the ERD/ERS and neural efficiency domain, alpha, theta, beta and SMR frequency domain in sports.

1.4.1.1 ERD/ERS and neural efficiency in the sporting domain

In 1967, Fitts and Posner reported three distinct stages of skill acquisition: a) Early cognitive stage; b) Intermediate associative stage; and c) Autonomous stage. The early cognitive stage is reflected by effortful processing, supported by a conscious regulation of movement. The intermediate associative stage reflects more proficient processing of the task and greater efficiency of movement execution. The autonomous stage reflects the transfer from conscious regulation of the execution of movement, to full automaticity of the movement. The model described by Fitts and Posner (1967) offers a theoretical account of the change that occurs as athletes move from novice to expertise. The theory emphasises that the ability to regulate movement, emotion and cognition are all important elements of expert behaviour. From this perspective, one of the key requirements for successful performance is the effective transition from a conscious to an automatic mode of behaviour.

A variety of studies in the sporting literature have focused on investigating the model presented by Fitts and Posner (1967). The studies presented below that support the model have demonstrated that neural efficiency underlies the development of sporting expertise. In general, most of the these studies have used paradigms that allow comparisons to be made between novices and experts, to investigate changes in brain activity as a function of expertise and to examine the association between expertise and the cognitive-motor control of behaviour in athletes. The neural efficiency hypothesis in the sporting domain posits that expert athletes' complete tasks with minimal effort in comparison to novice athletes (Bertollo et al., 2016). According to (Callan & Naito, 2015) reduction in neural activity has been suggested to reflect efficient processing during motor execution in athletes.

The neural efficiency in some studies been measured in terms of Event Related Desynchronization (ERD) and Event Related Synchronization (ERS). ERD/ERS has been defined as the percentage of power decreased (activation) or increase (inhibition) from baseline (Pfurtscheller & Lopes Da Silva, 1999). In support of the neural hypothesis, research has found ERD in alpha (8-12 Hz) in the frontocentral region for successful putts in comparison to unsuccessful putts within a sample of expert golfers (Babiloni et al., 2008). The findings of the research led to the conclusion that visuo-spatial areas are involved in the golf putting task and are related to golf putting performance.

In line with the neural efficiency hypothesis, Del Percio et al., (2009) compared expert versus novice shooters. The researchers reported that experts had exhibited global alpha power decrease during the pre-shot period compared to novices. The findings suggest that elite athletes are able to reach optimal levels of visuo-motor performances associated with lower cortical activation. Additionally, the authors had reported low alpha (8-10 Hz) ERD and high alpha (10-12 Hz) ERD across the whole scalp which was lower in elite athletes compared to novices. The pattern of results had been reported to reflect an index of spatially selective cortical activation, suggesting that preparation for visuo-motor performance in elite athletes is related to a smaller decrease of alpha power compared to novices. Overall, the researchers suggested that compared to novices, elite shooters engaged cognitive processes and areas that support optimal performance levels.

However, in some sport studies (Comani et al., 2014 ;di Fronso et al., 2016) ERD was defined as an increase of signal power, whereas ERS reflected a decrease of signal power in respect to a baseline. The definition provided by this line of research is based on the analysis of the data in ASA software, where ERD/ERS is based on Zanow and Knosche (2004) definition.

Bortoli et al., (2012) had proposed the multi-action plan (MAP) model which suggests that different performance levels are associated with unique behavioural and neurological patterns (Bertollo et al., 2013). The fundamental basis of the MAP model is a 2 x 2 (performance by control) relationship which is characterized by optimal and suboptimal levels of performance interacting with high and low levels of action control (controlled vs automatic execution). For example, optimal-automatic performance known as Type 1 in the MAP model, is characterized by smooth execution of the task in an automatic state leading to optimal levels of performance. Type 2 performance is known as optimal-controlled and is characterized by controlled execution leading to optimal performance levels. Suboptimal-controlled performance is reflected by excessive conscious control undermining the automaticity of the action and leading to suboptimal levels of performance. Finally, suboptimal-automatic (Type 4) occurs due to less effort execution reflected in the task leading to suboptimal levels of performance.

Di Fronso et al., (2016) had reported different neural patterns associated with the different performance types suggested by the MAP model. Type 1 (optimal-automatic) was characterized by ERS in alpha levels in parietal, occipital and somato-sensory areas at shot release. However, optimal-controlled (Type 2) state was characterized by increased alpha in the frontal and occipital areas, suggesting that expert athletes can successfully perform a task even when not in an automatic state, by focusing on the core components of the action. Surprisingly, the researchers had also reported that lower cortical activation and lower alpha levels were present for Type 4 state (suboptimal-automatic).

This stark difference in terms of ERD/ERS makes it really difficult to compare between any existing findings and leads to confusion when interpreting results within the sporting domain. EEG research in the sporting domain has largely focused on examining differences between experts and novices within the alpha frequency domain as will be described in the next section.

1.4.1.2 Alpha Frequency- Experts versus novices’ studies

EEG research in sport expertise has largely focused on investigating differences between experts and novices. The differences have been investigated in non-sporting related activities (Babiloni et al., 2010) and during sporting performance. For example, in 2010, Babiloni and colleagues (Babiloni *et al.,* 2010) compared elite karate athletes to amateur karate athletes and non-athletes, using EEG during an eyes-closed resting state to investigate alpha rhythms. The researchers reported greater amplitude of parietal and occipital lower alpha (8-10.5Hz) for elite athletes compared to amateur and non-athletes. Whilst differences in resting alpha are potentially interesting, the study raises a number of methodological issues. First, only one condition was used in the study, a resting eyes closed condition, and alpha levels are known to vary between individuals. Because the study did not examine alpha relative to a baseline measure of individual alpha frequency within each individual, any differences between the groups may simply reflect individual variability. Second, the study took part in a laboratory and did not engage the participants in any sporting behaviour. Nonetheless, Babiloni and colleagues argued ‘’the amplitude of eyes closed resting state alpha rhythms reflected the general efficiency of back-ground synchronization mechanisms in elite athletes’’ (Babiloni et al., 2010, p.154), supporting the hypothesis that cortical neural synchronization (in an eyes closed resting state) is enhanced in elite athletes compared to control subjects.

Following up on this initial report, further studies compared alpha measured during eyes-open compared to eyes-closed conditions, in both karate and non-karate athletes. Evidence from EEG revealed that karate athletes exhibited reduced alpha over frontal and central locations during the eyes open condition (Del Percio *et al.,* 2011b). However, the differences in alpha levels exhibited between athletes and non-athletes could reflect a number of factors, including pre-existing differences between individuals that lead them to be elite, changes due to training, or wider changes in cognitive ability unrelated to sporting behaviour *per se*. Within the sporting literature, however, the findings have been viewed as a specific consequence of the level of expertise and intensive training of the athletes. However, the wider EEG literature suggest that other factors may contribute significantly to differences in alpha power across individuals, including psychological, anatomical, and physiological factors (Bazanova & Vernon, 2013).

For pragmatic reasons, studies using EEG to measure actual sporting behaviour have largely been designed to investigate closed sports. Closed sports are self-paced sports such as shooting, golf, curling, archery, etc., which for EEG purposes minimize issues of equipment portability and movement artifacts (due to the nature of the sport). Importantly, because closed sports involve fixed routines (e.g., pick up the ball, aim, step back, step forward, kick) they provide researchers with an opportunity to measure the performance of the athlete during execution. In addition, because these sports involve multiple repetitions of the same routine, they allow brain activity to be averaged over many trials, time-locked in relation to the task in hand. Consequently, most of the EEG studies in the sporting literature have focused on investigating brain activity in the seconds leading up to the shot execution, known as the pre-shot period. For example, Haufler, Spalding, Santa Maria and Hatfield (2000) recorded brain activity during the pre-shot period in a simulation rifle shooting scenario and reported that expert shooters exhibited greater alpha power over the left-temporal electrodes compared to novices. The researchers had suggested the increase of alpha power of the left-temporal region reflected less cortical activation present for expert shooters during the aiming period. The pattern of results led the researchers to characterize experts as ‘’automatic performers’’ who do not rely on verbal-analytical skills and inhibit cognitive processed that are not relevant to the task.

In a review, Janelle and Hatfield (2008) examined a number of studies investigating the pre-shot period in target shooting. Most of the studies have shown that superior performance is associated with an increase of alpha power over the left-temporal region of the scalp. In the wider literature the left-temporal cortex has been related to verbal-analytical and language functions, whereas the right-temporal cortex has been linked to visuo-spatial processing (Springer & Deutch, 1998). Consequently, the changes in alpha power during target shooting have been linked to a reduction in overthinking and to the stabilization of the visuo-spatial coordination. This interpretation is also consistent with Fitts and Posner’s (1967) model of skill acquisition, which claims that elite athletes inhibit the verbal-analytical processes of aiming - because too much thinking would interfere with performance if inhibition did not take place. However, it is important to acknowledge that increases in alpha are not consistently related to improved performance in the sporting literature. For example, Salazar, Landers, Petruzezello, Han and Kubitz (1990) reported that increased levels of left-temporal alpha power during the pre-shot period and low beta power were associated with poorer performance in skilled archers.

1.4.1.3 Successful and unsuccessful performance

Most studies in the sporting literature have focused on comparing skilled to novice athletes. Recently, however, a number of studies have also examined changes in neural activity in relation to successful versus unsuccessful behaviour. For example, as noted above, in their 2008 study Babiloni and colleagues (Babiloni *et al.*, 2008) asked expert golfers to execute 100 putts on a golf green simulator, at a distance of 2.1 meters. The researchers had adjusted the hole for each participant, to ensure that 30% of the putts would have been unsuccessful. The authors reported that there was a decrease in upper alpha activity (10-12Hz) that supported successful compared to unsuccessful putts. The decrease of upper alpha activity was visible over frontal and central midline electrodes (Fz and Cz), as well as at a right central electrode (C4). The data also revealed that the decrease in alpha power correlated with the degree of error (defined as the final distance in cm between the golf ball and the hole) in the unsuccessful putts, suggesting a direct link between EEG data and performance.

Although the study by Bablioni *et al.* (2008) does provide evidence that the difference between successful and unsuccessful performance is reflected in changes in alpha, there are clearly a number of reasons to be concerned about the findings. As noted above, the ecological validity of the study is poor because the athletes were not tested in a normal sporting context - the researchers adjusted the size of the hole for each participant. Moreover, other studies have reported increases in alpha associated with superior performance, whereas in this case, superior performance was associated with a reduction in alpha power. Exactly how improvements in performance could be associated with both increases and decreases in alpha power is unclear; more importantly, this apparent contradiction is simply not addressed in the literature.

Inconsistencies are also apparent in relation to the scalp locations where performance related changes in alpha have occurred. As noted above, a number of studies have reported alpha increases over the left-temporal electrodes. By contrast, Loze *et al.* (2001) reported an increase in alpha at occipital electrodes in a study of successful versus unsuccessful performance in expert air-pistol shooters. Although the variation in scalp location could reflect genuine differences in the demands of different sports, inconsistencies also exist within a single sport. For example, Del Percio *et al.* (2009b) examined pre-shot activity in elite air-pistol shooters and non-athletes, reporting differences in alpha suppression across frontal, temporal, parietal, and occipital scalp locations. The study also reported an increase of upper alpha increase (10-12Hz) over right parietal and left-central scalp locations supporting successful versus unsuccessful performance (Del Percio *et al.*, 2009). As these examples illustrate, across studies there are clearly differences in the number and location of electrodes at which changes in brain activity have been reported.

According to Luck and Gaspelin (2017) a significant problem exists within EEG research because researchers often report data patterns that are in line with their hypothesis, even when the hypotheses were actually developed in relation to differences in neural activity at other specific electrodes. Concerns have also been raised within the literature regarding the way brain activity is characterised and interpreted. Notably, the brain activity bandwidths used across the sporting literature to define alpha has been inconsistent across studies. Some researchers use the traditional 8-12 Hz to define alpha, whereas other studies define alpha individually for each participant (e.g., using EEG recorded in eyes-open versus eyes-closed conditions to define the bandwidth of alpha), and still others split the alpha frequency into upper (10-12Hz) and lower ranges (8-10Hz). In combination with variability in the location and eliciting conditions, the variability in the definition of alpha means that it can be difficult to assess whether two different studies are examining and reporting equivalent brain signals.

1.4.1.4 Theta frequency in the sporting domain

In precision shooting (Air rifle, pistol) an important requirement is to align the barrel of the rifle to the target at the moment of the shot. This monitoring process in shooting has been associated with activity of the prefrontal cortex, which in turn has been quantified by examining the frontal-midline theta oscillations (around 4 to 7 Hz). For example, Doppelmayr *et al.* (2008) reported a link between pre-shooting frontal midline theta and rifle shooting performance. The study revealed that frontal-midline theta was higher for expert than novice Air rifle shooters, with a consistent increase of frontal-midline theta within the three seconds preceding shooting for experts, whereas there was an inconsistent fluctuation for novices. Although we acknowledge the important contribution of this Doppelmayr *et al.* (2008) study, a critical question remained unaddressed: how do changes in frontal-midline theta relate to successful and unsuccessful performance.

In the wider EEG literature frontal midline theta is most pronounced at the Fz electrode and is considered a direct index of attention. Studies have shown that in an eyes-open condition, frontal midline theta power increases with mental effort and concentration (Klimesch, 1999). According to Gevins *et al.* (1997) frontal midline theta power may be viewed as an indicator of attention processes and is likely generated in the anterior cingulate cortex. Consistent with this view, Baumeister *et al.* (2008) reported that expert golfers exhibit higher frontal-midline theta power compared to novices in a golfing task. The researchers suggested that experts have a superior ability to concentrate on relevant information, which leads to successful performance.

Notwithstanding concerns about the existing sports EEG literature, and the inconsistencies mentioned above, it is clear that changes in alpha and theta band power have been consistently linked to differences in sporting performance. At present, it remains unclear whether the differences in the pattern of alpha power observed across studies are due to differences in the sports being investigated, differences in the specific task demands of the sports being examined, or differences in methodology. Further research is needed to investigate the inconsistencies highlighted in this chapter, by following more precise guidelines around EEG data acquisition and EEG data analysis. To date the sporting literature has largely focused on identifying brain-behaviour links between groups of athletes (e.g., novices versus experts), or at best, by examining differences between successful and unsuccessful performance averaged across a group of elite athletes. From a sports perspective, however, the main goal is to understand brain-behaviour links within each individual athlete – understanding why performances are successful or unsuccessful, and identifying the cognitive and neural processes that lead to success.

Consequently, within the framework of this PhD, mobile EEG will be used to record and analyse neural signals both across- and within-individuals. Another significant methodological concern within the EEG literature is that many sports studies do not report all the key details of data processing. In particular, published sports studies (Crews & Landers, 1993; Haufler, Spalding, Santa Maria & Hatfield, 2000) do not mention their choice of baseline period (the period that is defined as zero voltage, from which any task related activity is then measured). Although cognitive EEG studies routinely include and report the baseline period, the sports literature does not do so, and it can be difficult to tell whether published data includes a baseline, and if so, what the baseline period was. Clearly, the choice of baseline period (as will be discussed in more detail in Chapter 2) can have a significant effect on EEG findings and the interpretation of results. The baseline period choice and the effect that this can have on results will be discussed further in the next chapter, including the processing pipeline used within the framework of this PhD.

1.4.1.5 Beta frequency, sensory motor rhythm

The human sensorimotor and cognitive behaviour is associated with changes within a number of different frequency ranges, not just alpha and theta. Of relevance to sporting behaviour is the fact that motor activity is associated with changes in beta frequency oscillations, ranging from 15-30 Hz. A voluntary movement has been reported to be associated with lower beta power (Davis, Tomlinson & Morgan, 2012). Consistent with this finding, studies in the neurofeedback domain appear to primarily investigate the relationship between beta (12-30 Hz) and focused attention (Thompson *et al.*, 2008). The sensory motor rhythm (13-15 Hz) has been of particular interest in the sporting literature, as a reduction in the excitability of the sensory motor cortex has been found to be associated with a sustained and relaxed attentional focus and more efficient performance overall (Thompson *et al.*, 2008). The sensory motor rhythm (SMR, 13-15Hz) is observed over the sensorimotor cortex, and according to Sterman (1996), is inversely related to the sensorimotor cortex activity. Higher sensory motor rhythm has been characterized as an adaptive state of refined task-related neural processing during psychomotor and attention-related tasks (Gruzelier, Egner & Vernon, 2006). For example, Cheng *et al.* (2017) investigated the SMR power for action execution in pistol shooters. Their results revealed that the best shooting performance (scores of 9 and 10) were preceded by higher SMR power (at the Cz electrode) during the last second before action initiation. The researchers suggested that the demonstration that lower activation in the sensorimotor cortex was associated with the best performance provides support for the neural efficiency hypothesis.

Given that the aim of studying sports is to obtain information that might help motivate changes in individual performance outcomes it is perhaps to be expected that sports professionals regularly employ neurofeedback, a technique for teaching individuals to modify their own neural activity (Park, Fairweather & Donaldson, 2015). Typically, neurofeedback paradigms consist of participants having their EEG monitored continuously, whilst being shown a representation of their brain activity on a computer screen (e.g., a beeping noise, or an image of fish swimming across a screen or a candle burning), providing the EEG participant with feedback about their current mental state. Over time, with practice, most individuals are able to learn to control their mental state (resulting in changes in the rate of beeping, movement of the fish, or flickering of the candle).

1.4.1.6 Neurofeedback in sports

Over the past few years, research hinted to the important and promising application of neurofeedback protocols within the field of sport psychology (Perry et al., 2011). In the next few paragraphs, we will provide an overview of studies that have attempted to use the neurofeedback technique and their limitations. Although the development of neurofeedback lies out-with the scope of this PhD, we firmly believe that the work presented within this PhD provides a step forward by validating sports biomarkers within real-world settings. The findings provided by the work performed for the purposes of this PhD, will lead in future research developing neurofeedback protocols that will improve performance.

The neurofeedback approach was first introduced in clinical contexts, aiming to treat anxiety and depression, etc. In sports, however, neurofeedback has been developed further, such that the aim is typically to train athletes to be able to produce ‘optimal’ brain patterns – with the desirable brain patterns defined on the basis of brain signals that have been associated with successful behaviour in EEG studies. The aim of neurofeedback is to allow participants to learn how their mental state correlates with their neural activity, by being able to control and maintain brain states, based on the assumption that athletes will then be better able to produce ‘optimal’ brain patterns during competitions. The neurofeedback technique has been slow to gain acceptance in the sporting domain due to lack of understanding and lack of research evidence outside the medical context (Perry et al., 2011). Given the concerns outlined in the previous sections above about the variable nature of the signals identified in EEG studies to date, it should be clear that the literature does not currently provide a solid basis for defining ‘optimal’ brain states.

To investigate how effective neurofeedback was for athletes Landers *et al.* (1991) examined its use in twenty-four pre-elite archers. Participants were split into three groups, a) Treatment - receiving correct feedback, b) Treatment - receiving incorrect feedback, and c) Control - receiving no feedback. The aim of the study was to record the alpha levels of the participants whilst making a series of shots, and neurofeedback was provided to the participants visually. The correct feedback treatment group received a single session of training, targeting the ability to reduce left-temporal alpha activity. By contrast, the incorrect feedback treatment group received training to reduce right-temporal alpha activity, and the control group received no training. The correct feedback group showed an improvement in performance, whereas the incorrect feedback group showed poorer performance after training, and the control group did not show any difference in performance. Increases of similar magnitude in alpha and beta power were recorded over the left hemisphere across all three groups. Interestingly, beta power increased over the right hemisphere in the ‘incorrect feedback’ group, but there was no such increase in the ‘correct feedback’ group.

In a similar study Rostami *et al.* (2012) compared the performance of 24 elite rifle shooters over a period of five weeks. Half of the participants were included in a treatment group and half of them in a control group. The treatment group received three, 60-minute sessions of sensory motor rhythm (13-15 Hz) training per week, whereas the control group did not receive any treatment. A significant improvement was reported in the performance of the neurofeedback group when examined post-training, whereas no difference was reported in the control group.

The studies that have investigated the effects of neurofeedback have examined the effects at a group level. As highlighted above, however, a critical issue for sports practitioners is to enhance sporting performance at an individual level. Many athletes can pursue and complete training routines, but not all the athletes will reach the highest level of expertise in their career. According to this view, elite athletes can be considered outliers, or atypical members of the wider population. Thus, from a sports perspective, it is necessary to understand whether the neural mechanisms underpinning successful performance can be trained via the application of EEG based neurofeedback technique at the level of the individual.

To date, however, to our knowledge only one study has investigated the application of EEG based neurofeedback technique at an individual level. Arns, Kleinnijenhuis, Fallahpour and Breteler (2008) recruited 6 amateur golfers and created personalized profiles by recording EEG activity from FPz electrode, whilst the golfers executed 80 putts. The personalized profiles were created by averaging the EEG across the 80 putts, and then identifying differences in frequency bands between successful and unsuccessful performance. Over three consecutive days the golfers then took part in neurofeedback during further putting practice, based on their personalized profiles. EEG was monitored during the putting pre-shot period and a tone was used to indicate when the golfer’s optimal neural pattern had been reached, meaning that the golfer should execute the putt. The participants performed four sets of 80 putts each day, either in a training or no training block, and the results revealed a significant increase in putting accuracy for the training compared to the non-training blocks – but only on day 2.

Despite being intriguing and somewhat promising, the results reported by Arns *et al.* (2008) also raise concerns, not least the fact that there was no benefit of the neurofeedback training on day 1 or day 3. The presence of significant change only on day 2 could reflect differences in the nature of the training sessions – which took place indoors on day 2, whereas on day 1 and 3 the sessions took place outdoors. The location of the practice clearly matters from a performance perspective, not least because changes in wind, light, noise, etc, all influence the difficulty of the putting task. For present purposes, therefore, the neurofeedback studies reinforce the importance of obtaining data in ecologically valid settings, but also emphasise the importance of examining individuals as well as groups. In the case of Arns *et al.* (2008), even though the profiles and neurofeedback were individually tailored, the assessment and interpretation of changes in performance was at a group level. This makes it difficult to assess whether the individually tailored profiles had any significant effect on the individual sporting performance of the athletes.

As this brief review highlights, although neurofeedback promises to be a valuable technique for sport, existing evidence leaves clear questions about its effectiveness. In particular, no specific frequency bands have been shown to have a clear relationship with performance, and the studies mentioned above each highlighted and investigated a different neural signal (either a different frequency band or different scalp location). Further investigation and validation of the neurofeedback technique is clearly required. Most importantly, however, at this stage it is crucial to better understand the neural mechanisms underlying successful performance at an individual level, at a group level and across different sports. In essence, gaining a better understanding of neural signals associated with successful performance is a prerequisite for the development of an effective neurofeedback protocol. In order to obtain optimal results through the use of neurofeedback, appropriate evaluation of an individual athlete's brainwaves will be required. Additionally due to the large diversity of skills required in different sports, the neurofeedback approach should not be considered as a ''one size fits all'' (Wilson, Thompson, Thompson & Peper, 2011). Thus, the investigation (within the scope of this PhD) of neural mechanisms underlying sporting performance in an ecological valid sporting setting across sports and individuals is an important step forward for future research and the development of optimal neurofeedback training protocols.

1.5 Emergence and current challenges of mobile EEG technique

The primary aim of this introductory chapter was to review the different neural patterns observed across the sporting literature. One of the main outcomes of this review was to highlight the variability in the pattern of neural activity reported by studies taking place in laboratory settings, and to stress the necessity of recording data in an ecological valid setting. Although the issue of ecological validity has been highlighted in the literature (e.g., see Clark, 1997) to date it has not been widely addressed in practice, in sporting contexts. Furthermore, concerns about a lack of ecological validity can also be related to concerns about the quality of existing EEG studies. There is a clear need for imaging data to be collected from athletes whilst they engage in real sporting behaviour, in ecologically valid settings. Moreover, as sports practitioners point out, when techniques like mobile EEG are used, it is critical that the equipment and paradigms do not interrupt the sporting activity of the athletes.

As noted above, recent advances in technology have made it possible to move EEG from laboratory settings to real-world settings. The emergence of compact, lightweight, and wireless hardware, that allow good quality recordings of the brain dynamics, have made testing and data collection in naturalistic environments possible. Although the advances in technology have made it technically possible to record data in naturalistic contexts, the traditional challenges faced in the laboratory setting in terms of data acquisition and analysis still remain as methodological challenges for mobile EEG. For example, during EEG data acquisition, horizontal eye movements, blinks and other muscle-related artifacts are prevalent sources of noise contaminating the EEG data, thus participants are advised to inhibit natural reflexes such as blinking (Picton *et al.*, 2000). In a laboratory setting instructions are given to participants to remain still and restrict any movement that is not associated with the behavioural performance of the task in hand, thus constraining natural behaviours such as blinking.

By contrast, instructions to remain still are necessarily avoided when brain activity is examined using mobile EEG data acquisition in naturalistic settings, because the aim is to allow behaviour to occur as it would without the EEG present. Whilst some kinds of behaviour (e.g., running) introduce so much movement that high quality EEG cannot be recorded, the limits of viable recording are currently unknown. Fortunately, progress in signal processing has made it possible to target and remove motion-related artifacts. For example, spatial filtering techniques such as Independent Component Analysis (ICA) can be applied to EEG data, leading to the dissociation of brain activity from movement artifacts (Makeig, Bell, Jung & Sejnowski, 1996). As we outline in more detail in the next chapter, ICA uses linear decomposition to separate EEG data into statistically independent components that can be identified as either noise or neural activity of interest.

Taken together, therefore, the development of mobile equipment and advances in signal processing have led to the possibility of recording EEG data during active sports performance. Despite the demand from sports professionals to understand brain-behaviour links and the factors contributing to sporting performance, sports neuroscience is still at an early stage (Jeunet *et al.*, 2020). As reviewed and argued throughout this chapter, there are substantial concerns regarding the consistency of findings within the literature, as well as concerns that undermine the use of neurofeedback techniques that are intended to improve performance. In addition, to date, the sports neuroscience literature has completely failed to examine or account for individual differences. Consequently, throughout this PhD, studies will focus on investigating differences in the brain activity underlying successful and unsuccessful performance at an individual level, a group level and in different sports.

Finally, we highlight that our use of mobile methods is intended to add value to traditional neuroscience research, by facilitating better understanding of brain-behaviour links in context. Mobile EEG can be used to overcome the major issue of ecological validity, enabling the brain activity of elite athletes to be examined in their own training environment. As a result, the paradigms used within this thesis have all been developed in association with the athletes (their coaches and performance managers), using their standard routines. This is important to avoid interfering with practice and preparation for competitions, but it also has practical implications. For example, in most sports the athletes do not practice until fatigued but do practice over many repeated sessions – providing the opportunity for examining brain activity within an individual over many sessions, or between individuals within a single session. Whilst engaging with elite athletes introduces constraints that would not be present in laboratory studies, we believe that the resulting data will demonstrate that sports neuroscience can provide useful insight into the relationship between neural activity and performance in real-world sporting environments.

1.6 Conclusion

To date, examination of the neural correlates of sporting behaviour has largely been limited to laboratory settings and artificial paradigms that are unrelated to sports performance. Attempts to examine EEG during sporting behaviour are relatively new, and whilst laboratory-based sporting studies have been valuable, the new mobile cognition approach used here promises to capture the complexity of real sporting behaviour in more natural sporting contexts. The present chapter has outlined why a move away from laboratory settings is important, given the rationale for examining brain activity in sport, and given the challenges within the current literature. The introduction of mobile EEG provides the opportunity to examine sport with increased ecological validity, using representative tasks that involve routine sporting practise. Consequently, the focus of this PhD is to use mobile EEG to investigate sporting performance across a number of different sports, to establish what kinds of sporting behaviours can be studied *in situ*, and to demonstrate whether there are consistent findings across individuals, and across sports.

Before introducing specific studies, the next chapter will focus on the data processing pipeline developed to address specific issues related to the acquisition and analysis of real-world EEG data. Our starting assumption is that the neural correlates associated with sporting performance in a real-world context will be different than in laboratory settings. Furthermore, we predict that neural dynamics of sporting performance will differ across sports and may also vary across individuals. From a cognitive neuroscience perspective, the significance of this PhD will be in demonstrating the viability of using mobile EEG for informing understanding of the cognitive and neural basis of sporting behaviour. We remain mindful however, that from a sports perspective, the ultimate aim is to use this understanding to improve the performance of individual athletes so that they can win more medals.

Chapter 2: Recording, processing, and analysing real-world EEG dynamics within a sporting context.

Mobile brain imaging methods offer exciting new research prospects, allowing researchers to explore areas of human cognition in ways that could not have been examined before. However, the real-world acquisition and interpretation of electrophysiological (EEG) signals in natural settings presents many methodological challenges. This chapter aims to detail the process developed within the framework of this thesis to address the challenges associated with recording EEG data in a real-world sporting context. One of the aims of the current thesis is to demonstrate that it is possible to use mobile EEG to capture brain signatures in sporting environments, during normal sporting activity. Consequently, we will describe how the brain signals were acquired, processed, and analysed to ensure the validity and reliability of the data. The structure of this chapter will reflect the progression from acquiring EEG data to analysing and investigating the signal quality of the data for each individual sport.

2.1 Methodological challenges of mobile EEG

Electroencephalogram (EEG) is a direct measurement of brain activity and a key requirement for interpreting brain activity is good signal quality. Traditionally the way to achieve good signal quality has been acquiring EEG data in highly controlled environments, such as a laboratory setting, where the participant is not required to perform any movement. This solution clearly limits the usability of EEG and excludes naturalistic behaviours. Over the past few years, EEG technology has advanced, and mobile EEG systems have been found to be reliable for recording brain activity in real world environments (Park et al., 2015). Thus, interest has risen in the field of sports towards recording neurophysiological markers of sporting performance in real sporting environments.

Whilst there is a growing interest in using brain imaging techniques such as

EEG to enhance sports performance, to date, studies examining the role of brain activity in sports have often used EEG as part of neurofeedback procedures, where athletes are trained to recognize and adjust their mental state (as indexed by specific patterns of EEG activity; see Park et al., 2015; Landers et al., 1991). Although the aim of these studies is to enhance performance, their success has been severely limited by a lack of basic understanding of what the neural correlates of successful performance are.

When EEG has been used to investigate the neural correlates of performance, neural data have typically been compared between expert and novice athletes (Park et al., 2015), rather than examining the neural activity associated with performance within individuals. These studies (discussed in Chapter 1) have also typically been carried out using laboratory-based paradigms (i.e., by simulating sporting behaviour, or using cognitive tasks, rather than actual sporting behaviour), thus limiting the relevance of the findings and underestimating the complexity of the neural mechanisms involved in real-world sport. Given the limitations of previous research, the new advances in mobile EEG technology provide the opportunity to study athletes' engagement in real sporting behaviour in a more ecological setting, thus overcoming the limitation of lab-based studies.

Mobile EEG clearly offers an exciting new research prospect, departing from the restriction of the laboratory and fully exploiting the portability of the modern technology. As noted above, one way in which traditional laboratory-based EEG studies established a good signal to noise ratio was by conducting experiments in highly controlled environments such as Air-Rifle shooting, Pistol shooting and Curling. One of the aims of the present research is to depart from the traditional restrictions and explore the feasibility of using the new technology in a number of different sporting environments. The typical constraints in EEG research, such as restricting the participants' ocular and bodily movements (to acquire high quality data) do not allow brain activity to be captured in naturalistic sporting environments. The aim of Chapter 2 is to outline the methodological challenges related to the acquisition of real-world EEG data and the solutions used to address the issues.

Given the challenges of mobile EEG in the investigation of real sporting behaviour, it is necessary to identify sports in which EEG data recording is viable. As noted in Chapter 1, EEG studies of sporting behaviour have focused largely on target sports such as golf, shooting and archery - these sports have been used because of their relatively low levels of movement (limiting the likelihood of artifacts) and because of their reliance on fixed routines. The use of a pre-performance routine is particularly important because it allows data to be collected across multiple repeated trials (essential for good EEG signal-to-noise ratio) and because it allows neural activity to be segmented over time in relation to the behaviour of interest.

Even in the context of low-movement target sports, it is preferable to focus on neural activity during the pre-shot period before movement is initiated – in essence this allows us to examine patterns of activity that lead to successful (versus unsuccessful) performance during the preparation period. The critical question for the novel studies carried out here is whether EEG data collection was viable when measured during actual sporting behaviour across a range of different sporting domains. A range of different sports was used to investigate the data quality (i.e., signal-to-noise ratio), including Air-Rifle Shooting, Pistol Shooting and Curling.

2.1.1 Acquisition of event-related brain activity in real-world context

In traditional laboratory-based EEG research, timestamping experimental events is a minor issue, as advancements in technology have led to stimulus presentation software that directly communicates the onset of events to the recording amplifier. However, timestamping EEG data in the real world represents a significant challenge. One solution to the problem of timestamping is to rely on other measurement methods (muscle contraction, eye movements). For example, electromyography (EMG) can be used to track the onset of muscle movements related to the task. EEG could then provide insight regarding the electrocortical activity related to motor execution in the real-world. Although advances in technology have supported the development of portable solutions for each of these methods, there are still technical issues that impede the successful synchronization with EEG.

One important requirement for the successful synchronization of different methods with the EEG is to be able to precisely align the different datasets in time. To achieve this, it is necessary for different types of recording devices to communicate with each other, sending triggers that mark key events within each system, synchronizing the different data events. Another crucial requirement is the need for equivalent high temporal resolution in each of the recording devices. In practice, different devices can have very different temporal resolutions (e.g., mobile eye trackers only sample behaviour every 10-20ms), leading to inconsistencies between the timing of the event and the marker, resulting in misleading analysis and interpretations.

Timestamping the events of interest for the purposes of this PhD was a significant challenge, due to the complexity of the sports and the researcher's aim of minimal signal involvement in the routine and equipment of each athlete. In practice, no single approach was feasible across all sports, and bespoke solutions were developed and tested for each sport. Pilot work involved testing different methods of timestamping of events. Electromyography (EMG), which is typically combined with EEG in laboratory settings, proved to be unreliable. In pistol shooting a more reliable and consistent approach was to use an acoustic sensor- that sends electronic triggers to the EEG recording device when the shots were taken by the shooters. By comparison for curling, manual triggering was performed (i.e., in curling the researcher pressed a button when the stone was released in order to timestamp the event of interest).

2.1.2 Movement artifacts during natural sporting behaviour

An advantage of recording EEG within a controlled environment (laboratory) is that many sources of movement-related noise are minimised-and those that remain are relatively easily-identified, because they exhibit specific characteristic scalp topographies that dissociate them from brain signals (e.g., eye movement activity exhibited at frontal electrodes). By contrast, muscular activity poses a more significant issue for mobile EEG recordings, and as would be expected, EEG recordings acquired in a sporting context display a wider range of muscle and movement-related sources of noise. In general, artifacts can be problematic for EEG recording and analysis, because they can decrease signal-to-noise ratio, thus limiting the likelihood of detecting differences across participants or conditions. Moreover, artifacts could be systematically present in EEG recordings contaminating one condition more than others and being time-locked to an event of interest, leading to misinterpretations of the data. For example, some stimuli might elicit more eye blinks, thus a difference between conditions could result from a difference in motor behaviour (related to producing eye blinks) rather than differences in brain activity. Given the problems artifacts can cause, it is crucial to detect and exclude data which include muscle artifacts from the EEG recording, to minimize the possibility of misinterpretation. The following section will present the data processing pipeline used in this research and the solutions that were implemented in order to effectively analyse EEG data recorded in a natural sporting context.

2.2 Acquisition procedure of ecological valid EEG data

The pre-processing steps followed in this thesis to address motion-artifact issues and investigate the signal quality recorded in different sporting contexts will be outlined in this section. It is crucial to select effective signal processing methods to ensure the validity of the outcome. The parameters employed in the processing steps were tailored to the data specifications and the research questions under investigation.

2.2.1 Recording Equipment Characteristics

EEG data was recorded through 32 Ag/AgCl electrodes, located on a headcap connected to a battery powered amplifier (ANT-Neuro, Enschede, The Netherlands). The sampling rate was 500Hz, and the data were pre-filtered with a high pass frequency of 0.012Hz and a low-pass filter of 250 Hz. Electrodes were positioned according to the International 10-20 system (Jasper, 1958). The ground electrode was placed on the AFz electrode, whereas the CPz electrode was used as the common reference site. Impedance levels were set below 10kΩ for all electrodes at the start of each recording session using ANT-Neuro's built-in impedance testing. EEG data pre-processing was conducted through EEGLAB (Delorme & Makeig, 2004) open-source toolbox and custom-made MATLAB scripts (version R2014b, The Math Works Inc.).

2.2.2 Processing Pipeline for mobile EEG data

Data processing includes a set of procedures applied to the EEG data prior to any analysis being carried out. These procedures aim to eliminate some types of artifacts that averaging or spectral analysis methods cannot deal with. In essence, the aim of the pre-analysis procedures is to produce a "clean" set of continuous EEG data. Below the procedures are described in detail, following the temporal order in which they were carried out.

2.2.2.1 Pre-processing of raw EEG data

The raw EEG data was retrieved from the tablet used to acquire the EEG data in the sporting experimental setting and processed on a PC. First, the continuous EEG file was merged with the trigger file (which contains time-stamping information about the events of interest that occurred during the data recording). At this stage, data from the mastoid electrodes was removed and all the remaining EEG was re-referenced to an average reference. In the sporting domain, the reference usually tends to be from electrodes placed on the either mastoids, the earlobes, or most commonly the average of all electrodes (Thompson *et al.,* 2008; di Fronso *et al.,* 2016; Jeunet *et al.,* 2020). Here in line with previous literature the average reference method was chosen. Visual inspection and manual rejection of the data was carried out to ensure that any noticeable brain signals contaminated with motion or other sources of noise/artifact were removed.

2.2.2.2 Filtering

In EEG research, filters are used to suppress noise contaminating the data and thus improving the signal-to-noise ratio of EEG data. Slow (low-frequency) channel drifts and fast (high-frequency) muscular contractions usually affect the EEG data. Band-Pass filters consist of low-pass filters, which attenuate high frequencies and pass low frequencies; and high-pass filters, which attenuate low frequencies and pass high frequencies. Notch filters attenuate some narrow band frequencies and pass all other frequencies and can be used to remove artifacts with specific frequency profiles (e.g., noise due to electric power supplies).

In ERP experiments, data filtering results in the minimization of residual high-frequency fluctuations. According to Cohen (2014) filtering is not always necessary, for example if there are many trials in an experiment. The method of averaging ERPs across multiple subjects also acts as a low-pass filter; because neural events are likely to have variable temporal characteristics across subjects, the average procedure effectively smooths the data. However, whilst filtering has advantages, it is important to acknowledge that it can also distort the signal of interest.

Another important caveat of filtering is that filters might not work properly when applied to short segments of data (e.g., individual trial epochs). Filters applied to short segments of data also introduces edge artifacts, thus, to avoid edge artifacts all filters were applied to the continuous EEG dataset.

A notch filter is used to attenuate electrical line noise and for the purposes of this research a 50 Hz Notch filter was used. Data acquisition within the Pistol, Air-Rifle and Curling paradigms was performed in indoor settings surrounded by electrical line noises from main currents, thus a notch filter was used to attenuate those specific frequencies. In addition, all data was processed using a band-pass filter, with a High-Pass filter of 1 Hz, a Low-Pass filter of 40 Hz and with a -6 Db roll-off. The selection of the filters used during the pre-processing stages was determined primarily by the frequencies of interest (alpha, theta, beta, Sensori-Motor Rhythm) that would be examined within the various studies. In the wider neuroscience literature (Luck, 2005) lower cut-off frequencies (e.g., 0.01 Hz) are typically recommended. However, for mobile EEG applications, Winkler, Debener, Muller & Tangermann (2015) recommend the use of a 1 Hz filter because this allows techniques such as Independent Component Analysis (ICA) to provide better results (in terms of the signal-to-noise ratio achieved). Additionally, as no examination of high gamma frequencies were to be performed setting a low pass filter at 40Hz is appropriate.

2.2.2.3 Independent-Component Analysis and the removal of artifacts

Independent-Component Analysis (ICA) is a model-based approach that decomposes patterns of activity based on differences in terms of topography, spectral activity, and time course (Makeig, Bell, Jung & Sejnowski, 1996). ICA can be used to clean EEG data by identifying components that isolate artifacts and subtracting those components from the data. The identification of artifactual components is based on their topographies and time courses. For example, eye blink related artifacts have an anterior scalp distribution (see Figure 2.1), and their time course is typically characterized by the presence of high-amplitude spikes.

When applied to EEG data, ICA reflects a set of weights from all electrodes, so each component is represented as a sum of activity from all electrodes, and the pattern of weights isolates specific sources of signal (Cohen, 2014).

Applying ICA to the EEG data provides the opportunity to differentiate non-brain signals from cortical activity. ICA can capture and isolate single Independent Components (ICs) that are sources of neural activity, as well as sources of electrical activity related to eye movements, muscle contraction and other sources of noise (e.g., bad channels due to high impedance).

The decomposition of the data is based on statistical properties; thus, ICA cannot determine which properties of the data are considered as “signal” and which properties to consider as “noise”. The EEG signal contains both signal and noise, thus the process of distinguishing and removing noise from the data requires judgements to be made about which components should be removed. Figures 2.1 and 2.2 show a representation of ICs (blinks and lateral eye movements). Within the framework of this thesis, ICA decomposition has been included in the processing pipeline and used to dissociate non-brain activity from signals of interest.

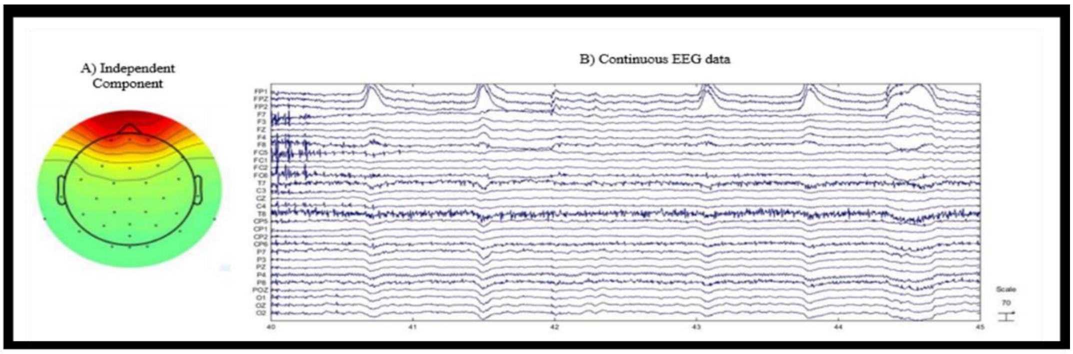


Figure 2.1. Independent Component Analysis decomposition of eye blinks related artifacts. [A] Spatial topographic activation artifact related to eye blinks decomposed into a single component. [B] Time series (5 second) pattern of activity related to eye blinks, prominent at frontal electrodes.

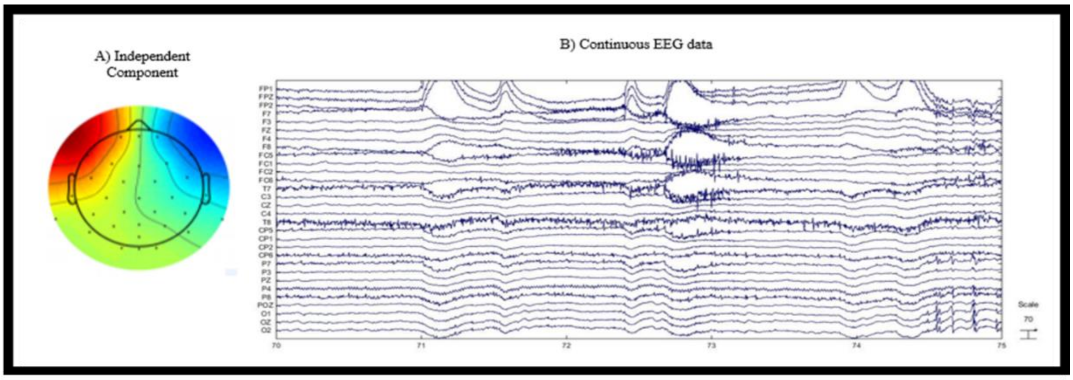


Figure 2.2. Independent Component Analysis decomposition of lateral eye movements related artifacts. [A] Spatial topographic activation artifact related to lateral eye movements decomposed into a single component. [B] Time series (5 second) pattern of activity related to lateral eye movements.

ICA produces better output results when applied to good quality data, as the ICs will reflect more of the weighted sum of artifacts rather than non-artifact signals. Even though ICA decomposition provides an effective way of detecting and rejecting artifacts, within the framework of this PhD, the SASICA (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact Correction, Chaumon, Bishop & Busch, 2015) plugin tool was used as an additional step of ICA decomposition, to support the selection and rejection of artfactual ICs.

2.2.2.4 SASICA

SASICA computes a series of measures on ICs topographies and time courses and automatically selects components for rejection. SASICA uses different measures that can be enabled or disabled allowing the tool to be tailored to the circumstances in which EEG data was recorded. Typically, components reflecting brain activity are strongly correlated with each other, contrary to noise components that tend to show lower correlation. The autocorrelation measure within SASICA computes the autocorrelation of each component at a specified lag (in ms) and when the value is below the specified threshold, the component is rejected. For the purposes of the present research, the autocorrelation method was selected using the default lag (20ms), and the threshold of autocorrelation was set to automatic, in line with the default measures proposed by Chaumon, Bishop & Busch (2015). Figure 2.3 reflects a representation of the raw EEG data prior to any pre-processing stages. Figure 2.4 reflects a representation of the data once pre-processing stages were performed including ICA and SASICA.

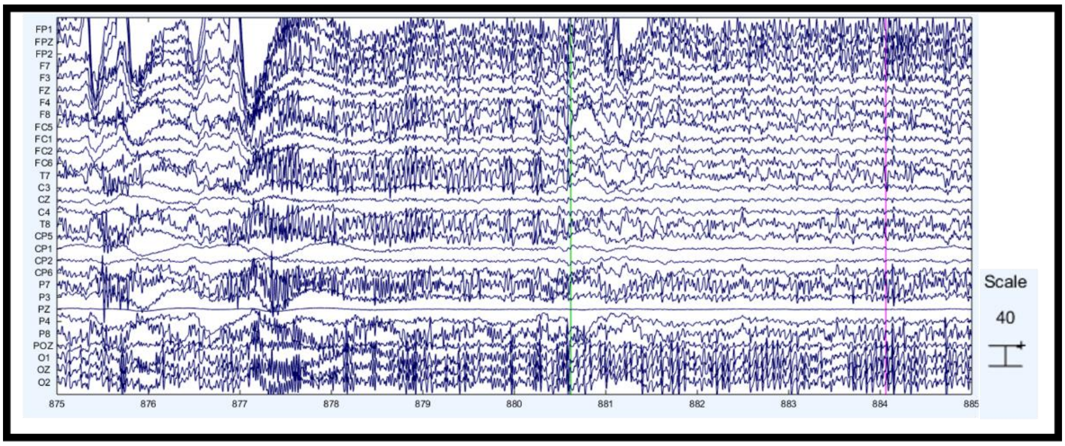


Figure 2.3. The figure reflects the raw EEG data prior to any data transformation. The green line reflects a trigger send when the curler pushed out of the hack and the red line reflects when the curler released the stone.

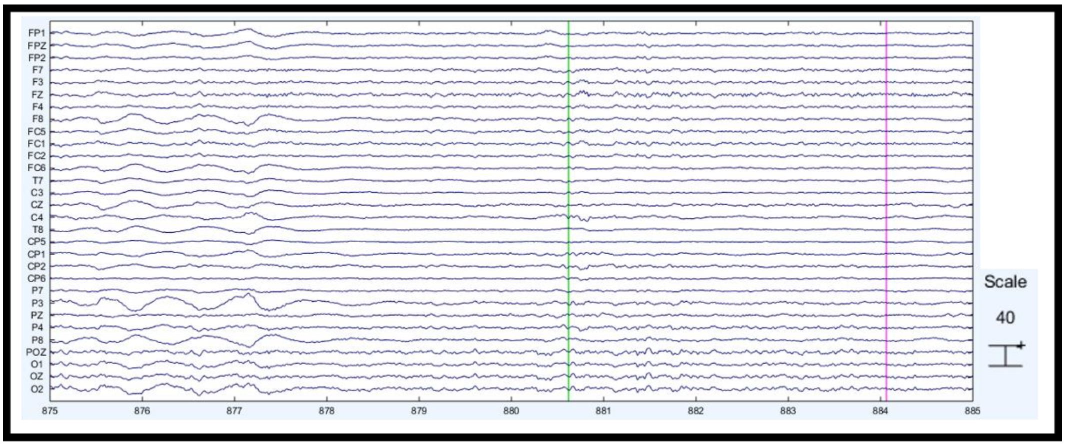


Figure 2.4. The figure reflects the EEG data after data transformation (including ICA and SASICA). The green line reflects a trigger send when the curler pushed out of the hack and the red line reflects when the curler released the stone.

The default threshold set in SASICA is 3 standard deviations and this value was employed throughout the thesis). For the purposes of this PhD, to ensure consistency across datasets and application of SASICA toolbox, any

ICs identified as artifacts were automatically removed from the data. Additionally, the ICs can be treated as single electrodes as they reflect linear combinations of the original electrode signal (Chaumon, Bishop & Busch, 2015). Thus, within the framework of this PhD the total number of ICs reflect the total number of electrodes used to acquire EEG data, which equals to 30.

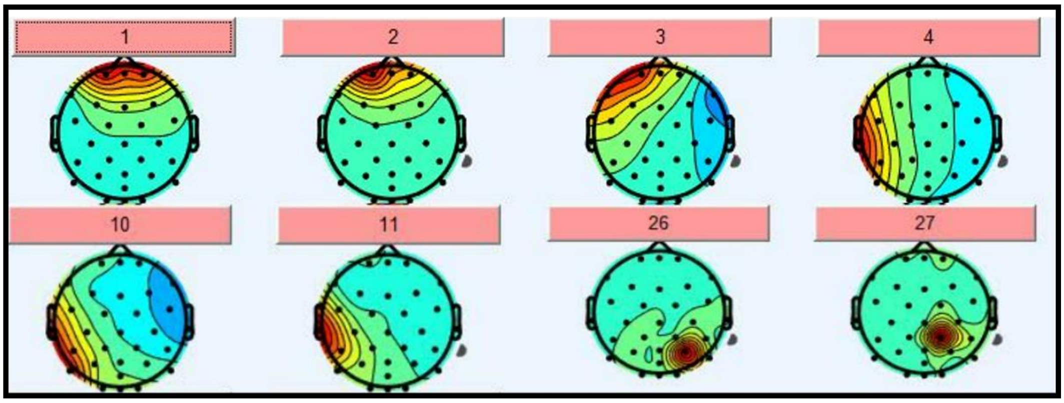


Figure 2.5. The figure reflects the components rejected through SASICA. The scalp topographies of the 8 selected components reflect eye artifacts in components [1] [2] [3] and muscle artifacts in components [4] [10] [11] [26] [27].

Figure 2.5 shows the components identified and rejected through SASICA. The eye movement artifacts are isolated to components [1], [2], [3]. The remaining ICs reflect the presence of noisy electrodes and muscle artifacts. The components have been identified through SASICA on EEG data acquired from a shooter. Air-Rifle shooting involves shooters resting their cheek on their Air-Rifle in a sideways manner which results in extending their neck on the left. Thus, as reflected in components [4], [10], [11] this neck extensions generate muscle artifacts on the left side of the head (i.e., where the extension occurs). Additionally, components [26] and [27] reflect noisy electrodes at the right side of the head because of the cheek resting on the Air-Rifle thus contaminating the EEG data.

A continuous challenge with acquiring and analyzing human electroencephalographic data is the presence of artifacts. Artifacts can arise from several sources such as eye blink, eye movements, muscle activity in the head and neck, electrical interference from external power sources or artifacts generated from electrode displacement. Within laboratory settings a variety of methods would be used to reduce artifacts such as asking participants to limit the number of times they blink or to remain still. However, a primary source of difficulty when acquiring EEG data in sports settings is the presence of physiological artifacts (Stone et al., 2018). It is impossible to ask participants to limit the number of muscle artifacts they generate in a real-world sporting situation when the task under investigation would inherently produce muscle activity.

Muscular contractions can be more intense and frequent when investigating EEG in sports compared to traditional EEG settings. Myogenic artifacts are generated by contractions of the head, neck and facial muscles, and head and neck movements are necessary for most sport activities such as in tennis (tracking the tennis ball), shooting (extending the neck muscles and head muscles to rest one side of the head on the rifle) and curling (extending the neck from a downwards movement to an upwards movement to track and focus on the target). Moreover, facial contractions are quite difficult to avoid in many sports applications and eyeblinks and eye movements are also difficult to limit. Moreover, artifacts generated by electrode displacements, cable movements and tensions due to sweating and movement, can have significant effects on signal quality (Stone et al., 2018).

Although, the number of artifacts in EEG sports science is significantly larger compared to traditional EEG settings, rendering the identification of physiological artifacts more difficult (Stone et al., 2018), the greatest advantage of Independent Component removal over conventional artifactual methods is the fact that an artifactual component is subtracted from the EEG data, without theoretically incurring any substantial loss to the remaining EEG data occurring simultaneously with it (Thompson et al., 2008).

Overall, no automated method can accurately isolate artifacts without human supervision, however, SASICA offers researchers the advantage of improving objectivity and reproducibility in their pre-processing steps reporting (Chaumon, Bishop & Busch, 2015) . Future work should focus on establishing an effective means of identifying physiological artifacts and separating them from brain activity within the domain of sports science and EEG by further improving ICA and developing an automatic classifier of physiological artifacts within the sporting science to advance the EEG signal processing in the field.

2.2.2.5 Epoching

EEG data can be collected and investigated at different time points, over different periods of activity (including changes in activity from millisecond-to-millisecond and consistent patterns of activity that last for seconds or longer). In practice, continuous EEG data are typically segmented into epochs associated with events of interest (stimulus presentation or behavioural responses). Extracting segments of EEG data relative to the event of interest allows the identification and characterization of brain signals related to specific cognitive processes. To achieve this the continuous EEG data are segmented into epochs around timestamps that mark the onset of the behavioural events of interest (typically related to different stages of performance). For this PhD, epoching was the final step concluding the pre-processing of the EEG data before proceeding to statistical analysis. Because the nature of the performance varies across sports, the timing and stages of interest also vary. For example, in Chapter 3 and 4 our studies examine shooting performance in pistol shooting. In line with previous literature the epoch of interest was set to -3000ms to 0 (the time at which the shot was taken), to reflect and follow what has been done in previous literature within the shooting domain (Del Percio et al., 2009).

By contrast, Chapter 5 focuses on investigating neural activity differentiating successful and unsuccessful performance in a curling task. Due to the fact that this is the first study to use EEG to investigate curling performance, the epoch of interest was identified through markers (triggers) used to establish the start of the task and visual inspection of the data established a time period from -2000ms to 0 (the time at which curlers' release the stone) which was not contaminated by muscle activity (due to the nature of the task).

2.3 Data Analysis

The previous sections focused on the stages of data acquisition and data pre-processing applied to the present research. A data analysis processing pipeline specifically adapted to the mobile EEG data of interest was also developed for the work presented here. The following sections will focus on introducing the parameters used for the extraction of meaningful signals from the epoched data. Traditionally, EEG research has focused on Event-Related Potentials (ERPs) in the time domain. By contrast, within the sporting domain, research has usually focused on examining spectral power in relation to the behaviour of interest over time (e.g., see Doppelmayr, Finkenzeller & Sauseng, 2008; Loze *et al.,* 2001). Consequently, within the framework of this PhD, a time-frequency analysis was performed. The time-frequency representation of EEG data retains information in both time and frequency domain. According to Cohen (2014), it is a good way to "*obtain temporally localized frequency information"*.

Morlet wavelets are an important component of time-frequency analysis of neural time series data (Cohen, 2014). Morlet wavelets are based on a similar principle as the Fast Fourier Transform, where wavelets of the same frequencies are compared to the signal and a coefficient reflecting their degree of similarity is computed (Cohen, 2014). The time-frequency analysis for the purposes of this PhD was performed by using Morlet wavelets (9 cycles at the lowest frequency and a maximum of 32 cycles at 40Hz for the highest frequency) across the epoch. The wavelet frequency ranged from 3Hz to 40 Hz with the number of wavelet cycles increasing from 3 to 32 following a 0.8 step increase (e.g. MATLAB code*: 'cycles', [3 0.8], 'freqs', [3 40], 'timelimits', [-6000 1000]*). In simple terms, the number of cycles within a wavelet is positively correlated with the frequency resolution.

Additionally, the wavelet length defines the temporal resolution of the time-frequency decomposition. The wavelets length is negatively correlated to the time resolution, thus shorter wavelets lead to higher time resolution.

Quantifying the brain oscillatory temporal dynamics would involve compromises between the resolution achieved in the time and frequency domain. For the purposes of this PhD, our interest focused on frequencies such as alpha and theta, most investigated in the previous sporting literature and more specifically the temporal transient changes. Thus, meaning that the lowest frequency will define the number of cycles that would enable to reach a satisfactory temporal resolution for the purposes of this PhD within lower frequencies, resulting to fewer cycles enabling the better detection and characterization of transient changes in the temporal domain. Additionally, we were also interested in frequencies such as beta which are not commonly investigated in the sporting literature; thus the higher number of cycles were more sensitive to changes at higher frequencies that would reflect frequency band specific changes.

The time-frequency analysis is advantageous for the purposes of this PhD as it measures dynamic changes in the amplitude of ongoing frequencies as a function of time, in relation to the sporting behaviour of interest. To simplify, time-frequency analysis will provide information on the neuronal changes within a time period in the EEG spectrum (Makeig, 1993).

2.4 Baseline correction

Time frequency plots are difficult to interpret across frequencies due to the 1/f shape the signal follows and can lead to limitations in interpreting the time-frequency, according to Cohen (2014). The 1/f shape refers to the fact that frequency spectrum data tends to show a decreasing power at increasing frequencies. This is called ‘the power law’, as power is a function of frequency. EEG time-frequency power follows the 1/f phenomenon, where power at higher frequencies tends to show a smaller magnitude compared to power at lower frequencies. Not only can this feature of frequency data make it difficult to visualize power across a range of frequencies, but it can also make it difficult to carry out quantitative comparisons of power across the frequency bands (Cohen, 2014). The reason for the aforementioned difficulty is that raw power values change in scale as a function of frequency – meaning that lower frequencies show larger effects than higher frequencies (Cohen, 2014). Moreover, raw power values are not normally distributed (they cannot be negative and are strongly positively skewed) which means that applying standard statistical analyses is not possible (Cohen, 2014).

The solution to address the issues of the power of law, is to use baseline normalization. Baseline normalizations transform the power of the data to the same scale, making it easier to compare (visually) the results from different frequencies, electrodes and conditions (Cohen, 2014). Traditionally, within the ERP domain, a baseline normalization would be computed by using a time period not associated with the experimental event, known as the pre-trial period (Cohen, 2014). Baseline normalizations are usually computed using a pre-trial period (i.e., a time segment not associated with the experimental event), allowing task-related changes to be dissociated from background activity. Following baseline normalizations, the results of power analysis can be presented using a standardised interpretable metric (and no longer violates the assumptions of standard statistical analyses). There are, however, several different ways of baseline normalizing the data within the EEG literature:

a) **Decibel Conversion:** The decibel (dB) is a ratio between the strength of one signal (frequency of interest) and another signal (baseline power of same frequency band). This approach is typically employed to describe the power of filters used during pre-processing.

b) **Percentage Change (%):** Percentage change results must be interpreted as changes in power relative to the power during the baseline period. The transformation of power to percentage change is computed by subtracting the baseline period power from the power of the period of interest, dividing by the baseline period power and multiplying by 100.

c) **Z-Transform:** Within the z-transform, power data are scaled to the standard deviation units relative to the power data during the baseline period. The results are usually presented in Z values but can also be converted into *p* values. The Z-transform is based on the mean and standard deviation of the baseline power over time.

In principle, the baseline period is a segment of time when little or no task-related processing is expected to occur. Given that the baseline is used to scale or normalise the activity measured during the period of interest, the choice of baseline can significantly influence the interpretation of the data, thus the choice of a baseline period depends on what is happening before and after the time of interest. The baseline period usually reflects brain activity in which the signal of interest is not present (Cohen, 2014). Given the importance of baseline corrections for the interpretation of EEG data it is somewhat surprising that, to date, the baseline correction method has not been widely used in the frequency-based analysis presented in the sporting domain. Indeed, the majority of studies in the sports literature do not mention a baseline normalization procedure. Consequently, in the current thesis both baseline (Chapter 3 - in line with previous literature), individual baseline (see Chapter 5) and non-baseline normalization (see Chapter 6) methods have been used, allowing us to examine the impact of baseline corrections and compare the present findings with the wider literature. For consistency across all these comparisons we use the percentage change approach because this has been used in studies within the sporting literature and it is the most easily interpreted of the different methods available (Babiloni et al., 2008).

2.5 Statistical Analyses

For the purposes of this PhD statistical analyses were performed using IBM SPSS Statistics, Version 27 (2020). Descriptive statistics were used to outline the mean, variability (standard deviation) and 95% confidence intervals of the datasets. The studies reported in Chapters 3, 5 and 6 all employ a within-subjects experimental design. Therefore, repeated measures ANOVAs and paired sample t-tests have been applied to the data, to investigate differences in the power of the EEG signals across levels of behavioural performance. The structure and conditions employed in ANOVA are outlined in the relevant chapters, typically involving multiple time windows, regions and electrode locations. Whenever t-tests are employed to directly compare successful and unsuccessful shots Bonferroni corrections are applied as appropriate and adjusted outcomes are reported.

Traditional statistical analysis relies on large sample sizes, examining group average effects. However, in many areas (such as studies examining neuropsychology patients or higher primates) researchers have to work with small samples (Ioannidis, 2013). For example, data collected from N-of-1 patient studies cannot be examined using group-based research designs, but patient data is often compared to the average of a control group. In the context of elite sports, our aim is to move away from group level comparisons towards the examination of individual athletes. In traditional group-based designs a large number of measurements are taken from a sample of many individuals. By contrast, in N-of-1 studies multiple measurements are taken repeatedly from the same individual (McDonald et al., 2020). From this perspective N-of-1 designs allow researchers to interpret individual differences by quantifying effects within and between subjects, resulting in richer data interpretations. Although it is not common, N-of-1 designs have been used in elite sports, for example Di Fronso et al., (2016) investigated differences across two levels of performance (successful/unsuccessful) within a shooting task with an N of 1. In this case the researchers relied entirely on visual inspections of the frequency scalp maps and described the pattern of activity characterizing the two levels of performance. To purse this individual athlete focused approach, in Chapter 4 of this thesis, two elite shooters will be investigated employing visual inspections of the data in combination with descriptive statistics such as the mean and confidence intervals to represent the amount of variability in the set of values have been used to provide a useful interpretation of the results (see Chapter 4 for detailed discussion of the issues around small sample studies).

2.6 Final Considerations

Two important conclusions can be drawn from the review of sports and signal processing. The first is that aspects of the processing methods used in any given study are often left unspecified in reports and articles, despite the significant impact that these choices can have on the outcome of the data analysis and interpretation of results (e.g., choices around baseline normalization are rarely reported). To be clear, it is crucial to fully document the methodologies used in EEG research, to facilitate data comparisons across studies and to ensure that the results are interpreted appropriately. Second, it is evident that to be effective the processing methods used in any given study needs to be tailored to the specificities of the data they are being applied to. Although the processing pipeline described in the current methodological chapter has been applied as consistently as possible throughout the framework of this PhD thesis, particular processing methods have been adjusted to meet the unique requirement of each sport (such as the epoch and baseline parameters employed within each individual study). Consequently, each of the following data chapters will include a methods section that specifies any variations in the parameters applied in the processing pipeline stages that have been described in the present chapter.

Chapter 3: Exploring the neural dynamics underlying performance during pistol shooting in a real-world shooting range.

3.1 Introduction

As previously highlighted, the majority of existing studies in the sporting literature explore differences in neural activity by comparing experts and novices. By doing so, researchers have identified neural markers related to expertise. More recently, however, studies have begun to focus on the neural activity underlying successful compared to unsuccessful performance within the domain of experts. A key issue is that typically the studies are undertaken in laboratory settings, which often involve tasks that are highly abstracted from real-world sporting activities and therefore findings do not necessarily translate into real-world contexts (see Chapter 1). Given these concerns, here we chose to record EEG during pistol shooting in an ecological valid setting (i.e., at an actual shooting range) and explore whether there are specific patterns of neural activity associated with different levels of performance.

A number of factors motivated the choice of sport. Firstly, the procedural routine associated with shooting involves a fixed series of steps, from raising the pistol towards the target to pulling the trigger that fires the gun. The procedural nature of shooting provides a clear and consistent time-locking point (i.e., the trigger pull), allowing neural activity to be examined in the period leading up to the shot. Secondly, shooting routines require the same shot to be taken repeatedly, providing multiple trials of equivalent data, which is a critical *requirement* for use of the signal averaging techniques commonly employed in neuroimaging research. Thirdly, shooting involves a relatively limited range of movement (the shooter has a single target and must maintain a steady aim prior to the shot), which is favourable for the recording of EEG data as the likelihood of muscular artifacts is lower than in sports that involve whole body movements. Taken together, these three conditions make shooting an excellent test case for exploring the potential markers underlying successful and unsuccessful performance during real sporting behaviour.

The following sections will introduce key EEG literature specific to shooting. The research surrounding the frequencies Alpha (8-12 Hz), Theta (4-7 Hz), Beta (15-30 Hz) and Sensorimotor Rhythm (13-15 Hz) in the shooting domain will be discussed, highlighting inconsistencies in the sporting shooting literature that have led to the rationale underlying this study.

3.2 Shooting studies

3.2.1 Alpha Frequency (8-12 Hz)

As noted above, to date EEG research into sporting expertise has found that there are differences in neural activity between experts and novices (see Chapter 1). In particular, the alpha power measured from left-temporal electrodes of experts has been shown to increase in the period leading up to the pulling of the trigger, an effect that is maximal just prior to the trigger pull (Hatfield *et al.,* 1984; described in further detail below). Consistent with this view, various studies have explored the characteristics of alpha power exhibited by athletes in different environments (simulated shooting tasks).

For example, in the case of Haufler, Spalding, Santa Maria and Hatfield (2000), EEG was recorded from fifteen (female and male) marksmen and twenty-one male novice shooters. The participants were asked to complete a shooting and two non-shooting tasks in a sound attenuated testing chamber. The shooting task consisted of 40 self-paced shots, in which the participant assumed a standing position and aimed towards a modified small-bore rifle target positioned 4m from the firing line. The researchers reduced the diameter of the target, as the shooting lane employed in the study was shorter than the standard 50ft. The participants were then required to complete a dot localization and word finding task. Both word finding and dot localization stimuli were projected on a screen positioned 4m away from the firing line. EEG was recorded from F3, F4, C3, C4, T3, T4, P3, P4, O1 and O2 electrodes. The researchers reported that during the aiming task experts exhibited an increase of alpha activity (less activation) compared to novices, which was more pronounced in the left central-temporal-parietal area during the aiming period. The significant differences found during the aiming period between experts and novices did not extend to the comparative verbal and spatial tasks (word finding and dot localization).

From the applied perspective of sport practitioners, simulating a shooting context (as in the example described above by Haufler *et al.,* 2000) sacrifices ecological validity and understanding that would be gained if data were acquired during actual performance. Haufler *et al.,* (2000) acquired data in a sound attenuated chamber and the shooting task consisted of the participant firing 40-shots in a standing position at a modified target 4 meters away from the individual. According to the International Shooting Sport Federation Technical Rules (ISSF General Technical Rules, 2020, p.3) ‘’the length of the range must be as exact as possible, subject to the following allowable variations: a) 100 yards (+/- 12 inches); b) 50 yards (+/- 8 inches); c) 25 yards (+/- 4 inches); d) 20 & 15 yards (+/- 3 inches); e) 6 yards (+/- 2 inches); f) 50 metres (+/- 0.20 m): g) 25 metres (+/- 0.10 m); h) 10 metres (+/- 0.05 m).” Clearly, the paradigm employed by Haufler and colleagues (2000) did not assess shooting performance under conditions that were representative of routine practice.

Previous literature provides a strong basis for interpreting alpha activity (see review by Janelle & Hatfield, 2008). For example, Cheron *et al.* (2016) provided a theoretical framework in the sporting literature for alpha oscillations, compatible with Crick’s searchlight hypothesis (Crick, 1984), suggesting that relaxed and focused athletes exhibit larger alpha amplitude before the successful execution of a motor task. Consistent with this view it has been suggested that effective cognition is not a function of how hard the brain works, but how efficiently it works (Del Percio *et al.,* 2011), known as the neural efficiency hypothesis (Doppelmayr *et al.,* 2005). Although it is beyond the scope of the present Chapter, it is important to note that additional support for the neural efficiency hypothesis stems from the wider non-sports literature, for example in studies showing that people with higher IQ exhibit greater levels of alpha power compared to individuals with an average intelligence score (Doppelmayr *et al.,* 2005).

In support of the characterisation of alpha as a neural marker of efficient processing, there is evidence within the sports literature that expert athletes’ complete tasks with minimal effort in comparison to novices (Del Percio *et al.,* 2008). One would expect that reduced effort and increased efficiency that characterizes expert athletes would be reflected in the quicker completion of the shooting tasks. However, the sporting literature does not provide any additional information that supports such a claim. As noted above, an early example of a change in alpha power was reported by Hatfield *et al*. (1984), who recorded EEG in international-calibre rifle shooters at four sites (T3, T4, O1 and O2), during the execution of 40 shots taken in a conventional indoor target shooting range (from a standing position). Analysis of the EEG revealed a progressive increase in left-temporal alpha power (8-12 Hz) during the final 7.5 seconds of the aiming period, but no significant changes at the right-temporal site, suggesting a hemispheric dominance when preparing to pull the trigger.

The neural efficiency hypothesis suggests that there is an inverse relationship between performance and resource allocation (Bertollo *et al.,* 2016). In broad terms, and consistent with the conclusions of Hatfield and colleagues (1984), the sporting literature includes several reports in which EEG patterns in expert performers exhibit a decrease in activation within the left hemisphere compared to the right hemisphere, during the preparatory period for self-paced motor tasks (cf. Haufler *et al.,* 2000). Consequently, the changes reported in alpha power during target shooting have been linked to a reduction of overthinking, consistent with the model of skill acquisition of Fitts and Posner (1967; see Chapter 1), which claims that elite athletes inhibit verbal-analytical processes during aiming - because too much thinking would interfere with performance.

Whilst the increases in alpha power observed during preparation to shoot are thought to be directly related to performance, it is important to acknowledge that much of the existing evidence stems from comparisons between experts and novices (e.g., Janelle & Hatfield, 2008). As noted in Chapter 1, however, comparisons between experts and novices are of limited value, particularly from an applied perspective where the focus is entirely on enhancing elite athletes' performance. Critically, links between alpha and inhibition during the pre-shot period are of interest precisely because they point towards a cognitive account of successful performance that coaches and performance managers can use to inform practice. From this perspective it is vitally important that future studies characterise the relationship between changes in alpha activity and shooting behaviour within elite shooters.

To date, there are only a limited number of studies in the sporting literature that have directly investigated the relationship between neural dynamics and performance. For example, Loze *et al.,* (2001) examined alpha power during the pre-shot period in air-pistol shooters at electrodes over the occipital region, examining the association with performance. Loze and colleagues (2001) recruited six air-pistol athletes and constructed a 10m shooting range in a purpose-built data collection building. The athletes were required to perform 60 shots individually, within a maximum period of 90 minutes, in accordance with the International Shooting Union rules. The researchers used four shot-quality indicators to choose the five best and five worst shots for the EEG analysis for each shooter. Their assessment derived from asking a sports psychologist to be part of the experimental team; this was an individual who had worked with the shooters prior to the study and was familiar with their training and competitive routine. The sports psychologist was asked to observe the performance of each participant and rate each shot. In addition, all athletes were asked to provide reports on the quality of each shot, regardless of the shot score. Furthermore, the experiment was recorded, allowing a post-hoc analysis of each participant’s technique during each shot to be carried out through video footage assessed by the sports psychologist. If the total of good and bad shots exceeded five trials, the researchers made an arbitrary decision to choose the first five from the 60-shot match. It is notable that despite their effort to construct an ecologically valid task (e.g., by building a shooting range) the procedures followed by Loze *et al.,* (2001) do not achieve a representative task design. At competition levels, performance is assessed based on all the shots taken and not just a select number of ‘best’ shots.

During their study, Loze and colleagues (2001) recorded EEG from only a limited number of electrodes (Oz, T3 and T4). Occipital EEG alpha power (recorded at Oz electrode) was found to increase during the pre-shot period of best shots, with a significantly greater increase during the last 2 seconds prior to the shot release (compared to a decrease prior to the worst shots). Based on this pattern of alpha the researchers suggest that athletes reduced their attention to external visual stimuli during the pre-shot of best shots, whereas they increased their visual attention during the worst shots. However, evidence from other studies challenges this finding. For example, Del Percio *et al.,* (2009) reported an alpha increase underlying successful performance, but only in the low frequency alpha range (8-10 Hz over left frontal, left central and bilateral parietal occipital areas) and the effect decreased during the last second prior to the shot. By contrast, high frequency alpha (10-12 Hz) was found to increase over left frontocentral and bilateral parietal-occipital areas, with a decrease in the right frontal-central regions and over the central-parietal midline underlying high performance.

As should be clear from the studies described above, the literature to date supports the view that changes in the alpha band are linked to differences in performance, but the nature of the relationship remains unclear, at least in part due to the inconsistencies reported across different studies. The inconsistencies that have arisen are mainly introduced by variability in the methodologies employed by each researcher. For example, as mentioned above, Loze *et al.,* (2001) investigated activity at the occipital region selecting the Oz electrode alone. By contrast, Del Percio *et al.,* (2009) employed a 56 electrode EEG system and investigated alpha activity at F3, F4, C3, C4, P3, P4, O1 and O2 electrodes. Given that the wider EEG literature demonstrates that oscillations in the alpha range can be detected over the entire scalp (cf. Nunez, 1995) the variable choice of electrodes is problematic. The comparison of the two methodologies outlined above highlights variability in the topographic distribution of the effects under investigation, making the results difficult to compare directly and leading to complications in the interpretation of results in the EEG sporting domain.

In fact, as can be seen in Table 3.1 across the literature there is a great deal of variability in the choice of electrodes employed, the epoch examined and the approach to baseline correction (which is often simply left unstated). The specific EEG measure under examination also varies across studies, including considerable modification in the way measures are calculated. For example, the ERD/ERS analysis procedures reported by Del Percio *et al.,* (2009) quantified the event-related changes (ERD/ERS) using the established procedure of Pfurtscheller and Neuper (1994). Typically, Event-Related-Desynchronization (ERD) refers to a decrease in spectral power relative to a baseline and Event-Related Synchronization (ERS) refers to an increase in spectral power relative to a baseline (Pfurtscheller, 1992). In stark contrast, however, in the cases of Bertollo *et al.,* (2016) and di Fronso *et al.,* (2016) ERD was defined as an increase of signal power, whereas ERS reflected a decrease of signal power in respect to a baseline. As this marked procedural difference makes clear, any comparison between findings is extremely difficult when the measures are defined so differently across studies. Further discussion of the methodological and analytical approach employed in the current study is provided in Section 3.6 and 3.7, after first highlighting findings in relation to other EEG measures.

Study	Participant and Task	Baseline	Epoch duration	Unit of measurement	Electrodes
Haufler **_et al.,_ 2000**	15 mixed-gender elite marksmen and 21 male novices, simulation shooting, visuospatial and verbal task	Not Stated	-6 seconds before trigger pull to 0 (i.e., trigger pull)	Alpha power	F3,F4,C3,C4,T3,T4,P3,P4,O1 and O2
Hillman **_et al.,_ 2000**	6 male and 1 female skilled marksmen Simulation shooting	Subtracting average amplitude for the 1s epoch, from each data point in the epoch.	-4 seconds to 0 (i.e., trigger pull)	Alpha power	F3,F4,C3,C4,T3,T4,P3,P4,
Kerrick **_et al.,_ 2001**	8 skilled marksmen, Airrifle shooting	Not stated	-8 seconds to 0 (i.e., trigger pull)	Mean alpha power	C3,C4,T3,T4
Loze **_et al.,_ 2001**	6 elite mail pistol shooters	Not stated	-6 seconds to 0 (i.e., trigger pull)	Alpha power	T3,T4,Oz
Deeny **_et al.,_ 2003**	10 expert and 9 less skilled marksmen Shooting from 5 meters away with target size adjustments.	Not stated	-4 seconds to 0 (i.e., trigger pull)	Coherence analysis for low (8-10 Hz) and high (10-12 Hz) alpha	F3, F4, Fz, C3, C4, Cz, T3,T4,P3,P4,Pz,O1, O2
Deeny **et al., 2009**	13 male and 2 female expert marksmen and 21 malenovices. Shooting from 4 meters away with target size adjustments.	Not stated	-4 seconds to 0 (i.e., trigger pull)	Coherence and phase angle analysis low alpha (8-10 Hz) and high (10-12 Hz) alpha	F3, F4,C3, C4,T3,T4,P3,P4,O1, O2
Del Percio **_et al.,_ 2009**	18 pistol shooters and 10 novices.	-5 to -4 seconds prior to trigger pull	-3 seconds to 0 (i.e., trigger pull)	ERD/ERS alpha power successful and unsuccessful performance and between groups	F3,F4,C3,C4,P3,P4, O1,O2.
Comani **_et al.,_ 2014**	3 elite air pistol shooters	-5 to -4 seconds prior to trigger pull	-3 seconds to 0 (i.e., trigger pull)	ERD/ERS alpha power	Prefrontal, frontal, central, parietal & occipital regions

Bertollo *et al.,* 2016	6 male and 4 female shooters.	-5 to -4 seconds prior to trigger pull	-3 seconds to 0 (i.e., trigger pull)	ERD/ERS Low/high alpha.	32 electrodes; 10-20 montage
Di Fronso *et al.,* 2016	1 male air-pistol shooter	-5 to -4 seconds prior to trigger pull	-3 seconds to 0 (i.e., trigger pull)	ERD/ERS Low/high alpha.	32 electrodes; 10-20 montage
Woo & Kim, 2017	8 male volunteers and 8 female high school air pistol shooters	Average of interval	-5 seconds to 0 (i.e., trigger pull)	Inter/intra hemispheric cortical communication low/high alpha power.	F3, F4,C3, C4,T3,T4

Table 3.1. Overview of differences in EEG analysis across studies using EEG in shooting (Alpha Frequency)

Table 3.1 does, however, illustrate another key issue: the total number of participants recruited for the purposes of investigating the alpha frequency in a shooting task. In the wider neuroscience literature, the number of participants is higher than in the sporting domain. For example, in a typical investigation of episodic memory using EEG data by MacKenzie & Donaldson (2016), the results were based on a total of 24 participants. Clearly, a key challenge in studying elite athletes is the small sample size available – the nature of competitive sport means that very few athletes are considered good enough to perform at an elite level. As seen in Table 3.1, the number of expert participants recruited varies (N=1-18) across studies. Consequently, in line with previous literature and the limitations arising from studying such a focused expert group of individuals, in the current study we will be examining the neural correlates associated with successful and unsuccessful performance in 15 expert shooters.

3.2.2 Theta Frequency (4-7 Hz)

Having outlined the important but poorly characterised role of alpha, we now briefly introduce theta as a second signal that has been linked to sporting performance in the existing literature. A wide range of studies have demonstrated the importance of theta for cognitive processing (e.g., for reviews see Klimesch *et al.,* 1994; Basar, 1999). Theta is particularly pronounced at frontal midline electrodes (e.g., at Fz), where it is often known as the frontal midline theta rhythm (or Fm θ). Studies in the wider neuroscience literature have shown that frontal midline theta power increases during eyes-open resting conditions, reflecting changes in mental effort and concentration (Klimesch, 1999). More broadly, according to Gevins *et al.* (1997), frontal midline theta power can be considered an index of attention and is likely generated in the anterior cingulate cortex.

From the perspective of sporting behaviour, the ability to focus one's attention on external sensory information is considered to be crucial for success at an elite level. Particularly relevant here, the air rifle shooting task is viewed as being highly complex, demanding an integration of visual input, postural balance and the timing of the trigger pull (Luchsinger *et al.,* 2016). In broad terms, therefore, the characterisation of theta as reflecting cognitive effort fits well with theoretical accounts of shooting. In particular, the attention-related monitoring processes required in the shooting task (for the required aiming adjustments) are argued to reflect activity of the prefrontal cortex, as revealed by the examination of frontal-midline theta oscillations (Cavanagh & Frank, 2004).

Although changes in theta power have been linked with expertise in the sporting domain, the evidence to date is limited. In the Haufler *et al.,* (2000) study, higher frontal theta activity in expert shooters compared to novices was related to higher levels of focused attention during the aiming period of a shooting task. Similarly, Doppelmayr, Finkenzeller and Sauseng (2008), reported differences between pre-shot frontal midline theta (from 4 to 7 Hz) in expert and novice athletes. The study revealed that frontal-midline theta (at Fz) was higher for expert than novice shooters, with a consistent increase of frontal-midline theta within the three seconds preceding shooting for experts, whereas there was an inconsistent fluctuation for novices. The change in frontal-midline theta was interpreted as reflecting the focussing of attention during the lead up to the shot: in precision shooting tasks (such as air rifle and pistol shooting) it is necessary to align the barrel to the target at the moment of the shooting – and this requires concentration.

Luschinger and colleagues (2016) compared frontal theta activity between biathletes (experts) and cross-country skiers (novices) during shooting to examine the effects of vigorous exercise between the two groups. The researchers recruited nine biathletes and eight cross-country skiers and compared brain activity during shooting in biathlon during a rested state and after vigorous exercise. Frontal theta (4-7 Hz) activity was compared whilst firing 100 shots in a 5m indoor shooting range, followed by 20 shots after five six-minute roller skiing sessions on a treadmill (practicing skating technique on treadmill). Biathletes performed better compared to cross-country skiers and their superior performance was accompanied by higher frontal theta power at Fz, from 2 seconds prior until 1 second after the trigger pull, indicating higher levels of attention in experts (biathletes) compared to novices (cross-country skiers).

As the preceding review highlights, the existing literature examining theta in a shooting context has largely focused on examining differences between experts and novices. As a result, the increases in theta power that have been reported in the literature have not been related to improved sporting performance *per se*. Although we acknowledge the important contribution of the previously mentioned studies, to our knowledge no studies in the shooting sporting context have directly examined whether high frontal-midline theta is an index of successful shooting performance in elite athletes.

3.2.3 Sensorimotor Rhythm (13-15 Hz) and Beta Frequency (15-30 Hz)

Neural oscillations between 13 and 15 Hz, often termed Sensorimotor Rhythm (SMR), reflect the preparation, execution, and imagery associated with a motor act, and are typically recorded from electrodes placed over the sensorimotor cortex (e.g., C3 & C4). It is important to acknowledge, however, that the SMR frequency range overlaps with (and may be difficult to distinguish from) alpha band (8–13 Hz) and beta band (15–30 Hz) activity, each of which displays different functional properties. Beta band activity is associated with the cognitive control processes supporting muscular activity (Klavik *et al.,* 2013). Overall, the wider research literature suggests that beta occupies a central position for the processing of sensorimotor information (Cheron *et al.,* 2016), playing a significant role in motor control and movement preparation. Of particular importance for present purposes, changes in beta power have also been reported in sports specific studies. For example, Del Percio *et al.,* (2009) reported a decrease of beta amplitude during the aiming phase of a shooting task (an effect that was significantly smaller in elite athletes than novices) suggesting that expert's engage areas appropriate to the task, leading to successful visuo-motor performance.

Notwithstanding concerns about the separation of SMR from beta activity, the wider literature has established a specific link between the SMR and motor activity. SMR has been shown to be inversely related to activation within the sensorimotor cortex,- (Kober *et al.,* 2015). More importantly for present purposes, changes in SMR have also been reported in sport related EEG studies. For example, Cheng *et al.,* (2017) examined different levels of SMR power during best and worst skilled air-pistol shooting performances, in 24 skilled shooters with an average shooting experience of 3.8 years. SMR power was assessed solely at the Cz electrode; the analysis revealed that the best shooting performance was associated with higher SMR power during the last second prior to action initiation. Additionally, SMR power was negatively correlated with the average distance of the shot from the bull's eye. Based on these findings the researchers suggested that superior shooting performance requires 'psychomotor efficiency', reflecting lower activation in the sensorimotor cortex, as indexed by higher SMR power.

Whilst it may not be possible to entirely separate SMR from beta activity, the focus on SMR reflects, at least in part, a desire to develop theoretical accounts of sporting performance. As noted above, the sports literature has highlighted neural efficiency as a key difference between expert and novice athletes. Baumeister, Reinecke, Liesen & Weiss (2008) reported that low activation of the motor planning related cortical areas contributes to greater consistency of motor performance. From this perspective, sporting success results from superior cognitive-motor processing, which leads to expertise (Hatfield & Hillman, 2001). As should be clear from the discussion so far, however, there is clearly a need for future studies to examine SMR within elite athletes, to assess whether the psychomotor and neural efficiency theories can explain the differences in processing that underlies successful performance.

3.3 Issues arising in shooting: EEG methods and rationale for present study

Over the past few decades, the development and application of pre-performance routines in sports has been an area of considerable interest to sports psychologists. In 1996, Moran defined pre-performance routines as "*a sequence of task-relevant thoughts and actions which an athlete engages in systematically prior to his or her performance of a specific sports skill*" (Moran, 1996, p.177). This definition highlights the important aspects of both cognitive processes and behavioural routines that lead to successful performance. From this perspective, understanding the EEG signals that are related to the pre-performance period should offer invaluable insight into the psychological strategies employed by athletes and reveal what distinguishes successful from unsuccessful performance at a neuronal level.

Although EEG research examining shooting has provided some insight and understanding regarding the neural mechanisms differentiating experts from novices, the differences reported in the literature are not sufficient to confirm the mechanisms responsible for dissociating different levels of performance (i.e., distinguishing between successful versus unsuccessful shots). Moreover, whilst existing studies of shooting have largely focused on the alpha frequency domain, even here current findings are not entirely clear. For example, it is important to acknowledge that increases in alpha are not consistently related to improved performance in the sporting literature, even though the dominant view in the shooting literature is that better performance is linked to an increase of alpha activity.

One conclusion that can be drawn from the existing literature is that future studies need to broaden their analyses of the EEG spectrum, to facilitate new insights being drawn from activity outside the range of the 8-12 Hz alpha frequency. Although, the findings from Doppelmayr and colleagues (2008) add significant insights into the differences in frontal midline theta and expertise, there is clearly a need to better understand whether theta also plays a role in explaining successful and unsuccessful performance. Similarly, research in the SMR range is also extremely limited. To our knowledge only one study has investigated the relationship between SMR power and shooting performance, thus there is a need for further exploration and understanding of the neural mechanisms underlying successful and unsuccessful performance. Consequently, given the paucity of existing evidence, one aim of the current investigation will be to examine each of the different frequency bands, with specific reference to successful versus unsuccessful performance in elite shooters.

Concerns can also be raised about the methods used in the shooting EEG literature based on the variability of locations and electrodes chosen, the choice of a baseline (if stated), and the differences in epoch duration amongst studies. Each of these issues is discussed in detail in the relevant methods section below, but here we briefly summarise the rationale for the approach taken in the current study. First, to allow a comprehensive examination of the pattern of EEG across the scalp in the current study we employ 32 electrodes. This approach allows us both to examine specific electrodes highlighted within the literature and to capture the topography of effects across the entire scalp. Second, the bandwidths used across the sporting literature to define alpha, and theta have been inconsistent across studies. Some researchers use the traditional 8-12 Hz to define alpha and 4-7 Hz for theta, whereas other studies define alpha individually for each participant (e.g., using EEG recorded in eyes-open versus eyes-closed conditions to define the bandwidth of alpha), and still others split the alpha frequency into upper (10-12 Hz), lower ranges (8-10 Hz). Consequently, here we focus on examining *a-priori* frequencies as stated in the wider neuroscience literature and sporting literature: Theta (4-7 Hz), Alpha (8-12 Hz), SMR (13-15 Hz) and Beta (15-30 Hz).

As is clear from Table 3.1, existing studies examine the pre-shot period using an epoch that ranges from 3 to 8 seconds in length, with the most common epoch being to examine the final 3 seconds leading up to the shot. Consequently, to allow comparison with the existing literature, here we also employ a 3 second epoch in the current study. Similarly, existing studies vary in their use of baseline period. Whilst many studies do not employ any baseline correction, the most common baseline approach is to use a period from -5 to -4 seconds before the shot. Again, therefore, following the wider literature, here we also employ a -5 to -4 second baseline period. Finally, as noted above, Table 3.1 highlights the considerable variability in the EEG measures examined, ranging from power in standard frequency bands to coherence analysis and derived measures such as ERD/ERS – making it difficult to assess whether the studies reported in the sporting literature are examining equivalent brain signals. Given the lack of consistency in how the more complex measures have been applied (as discussed in detail above), here we focus on the more common measure of power (measured across multiple frequency bands).

In sum, the overall aim of this study is to try and increase the ecological validity of the experimental task design used to examine the neural correlates of sporting behaviour (see Chapter 1 for detailed discussion of the ecological validity limitations in the literature). Given this aim, the current study examines a cohort of elite level pistol shooters during routine training. Critically, through discussion with athletes and coaches we established a set of EEG data collection procedures that could be integrated into existing training routines and would not interfere with, or alter, the training practice. Because of the concern about small and varied sample sizes within previous shooting studies we established links with two distinct groups of shooters (in Cyprus and Italy), providing a relatively large sample of 15 shooters (at the top end of the range outlined in Table 3.1). The research question underpinning the study is: “What are the performance-related differences in EEG frequency data during the pre-shot preparatory period leading up to pistol shooting?” Our aim is to examine this question across the frequency bands of alpha, theta, SMR and beta, providing a more detailed and comprehensive assessment than has been reported to date.

3.4 Methods

3.4.1 Participants

Fifteen skilled (3 Males, 12 females) pistol shooters took part in the Pistol shooting task. The participants were recruited from associations in Cyprus and Italy. All participants were right-handed and right eye dominant and had normal or corrected-to-normal vision. Mean age was 20 (S.D. ± 5). Average years of experience was 6 (S.D. ± 5). The experiment was reviewed by the General University Ethics Panel of the University of Stirling. The athletes took part in the research voluntarily, understood the experimental process and purpose, and provided written informed consent to participate.

3.4.2 Experimental Design

The shooting ranges were located In Nicosia (Cyprus) and Rome (Italy). All procedures followed the International Guidelines (ISSF General Regulations, 2020, p.6) of the shooting association. The 10-metre pistol shooting task consisted of 30-80 shots towards an electronic target. EEG data were collected using an ecological valid task design, based on the athletes' standard training routines. The participants were asked to follow their normal routine whilst performing the task, to keep the experimental sessions as close to the naturalistic setting of the sport as possible.

EEG activity was recorded continuously throughout practice, with time-locking triggers generated by a custom-built acoustic box and through a manual button press trigger, when each shot was fired. The custom-built acoustic box could not dissociate the sound from the gun fired and other surrounding noises (e.g., other shooters), thus, a manual button press was performed by the researcher each time a shot was fired to mark the events sent by the acoustic box. The triggers used to mark the EEG events were the ones sent by the acoustic box, ensuring precise timing.

The score associated with each shot was recorded, allowing EEG data to be examined as a function of performance. For the purpose of this research, performance was categorized into successful and unsuccessful levels based on a grand average mean, which was calculated across the average behavioural performance in each of the 15 participants. Since existing EEG literature has largely focused on comparing experts to novices, a standard approach to the categorization of successful and unsuccessful performance does not exist (e.g., see discussion of Loze *et al.,* 2001, above). From an applied perspective, and in real competitions, performance is always assessed on all shots taken. Thus, with the agreement of the athletes and coaches, and to ensure that there were sufficient trials in all conditions, we employed the grand average mean to categorise successful and unsuccessful performance. Importantly, however, as this study attempts to examine neural activity underlying successful and unsuccessful performance in a group of individuals a grand average mean was adopted (rather than defining success independently for each participant based solely on their own mean performance).

3.4.3 Material

EEG data was recorded through 32 Ag/AgCl electrodes located in an adaptable headcap and connected to a battery powered portable amplifier (ANT-NEURO, Enschede, The Netherlands). The digitized sampling rate of the system was set at 500 Hz, and data were recorded with a high pass filter of 0.0016 Hz and low pass filter of 250Hz (under the Nyquist frequency). The electrodes were positioned according to the International 10-20 system (Jasper, 1958) (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2). Electrode AFz served as the ground electrode and CPz as a common reference site. Electrode impedance was measured prior to each recording session and each channel was maintained below 10 kΩ.

3.5 Procedure

Prior to the experiment, the participants were given verbal and written information regarding the functional and practical aspects of the electroencephalography technique. Moreover, the participants, were informed that they had the right to end their participation in the study at any time without any consequences. Participants were then invited to provide their written consent to confirm their voluntary intention of taking part in the study.

The capping procedure lasted approximately 45 mins, during which participants were seated on a chair in the shooting range. Measurements of the participants' head were used to set up the electrode locations according to the International 10-20 system (Jasper, 1958). The electrodes were filled with conductive gel, and the experimenter used a disposable blunt needle to increase the sensor conductivity. The experimenter also checked that the electrode impedance was below 10 kΩ for each channel, adding additional gel if necessary.

Following the capping procedure, participants were then asked to undertake a short training session to warm up, which consisted of 10-20 shots towards an electronic target. The participants would let the experimenter know when they felt ready to start the experiment. Participants were instructed to follow their normal training routine and to take breaks between every 10 shots if necessary. Once data collection was completed the electrode cap was removed and participants were debriefed. The EEG data was then exported using the built-in data acquisition software (ASA, ANT-neuro). Continuous data was then stored on an encrypted hard drive, before proceeding with further processing.

3.6 Data Processing

EEG data were analysed using the EEGLAB open-source toolbox (Delorme & Makeig, 2004) and custom MATLAB scripts (version 2014, The

Mathworks Inc.). At the pre-processing stage, the continuous data were visually examined and segments that displayed obvious noise (e.g., channel disconnections) were manually rejected. Following the removal of noisy data, the datasets were then filtered with a low pass filter of 40 Hz and a high pass filter of 1 Hz. In the wider neuroscience literature (Luck, 2005) lower cut-off frequencies (e.g., 0.01 Hz) are typically recommended. However, the advent of mobile EEG has led to the requirement for additional artifact rejection and Winkler, Debener, Muller & Tangermann (2015) recommend the use of a 1 Hz filter because this allows techniques such as Independent Component Analysis (ICA) to provide better results (in terms of the signal-to-noise ratio). For example, ICA can be affected by non-stationary effects (such as sweating) which contaminate low frequency EEG data below 1Hz.

After initial pre-processing, Independent Component Analysis (Bell & Sejnowski, 1995) was performed on each dataset, identifying a set of Independent Components (ICs) (e.g., a total of 30 components for each dataset) for consideration as artifacts. The ICs were assessed using SASICA (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact Correction, Chaumon, Bishop & Busch, 2014) to identify artifactual ICs for rejection. Although SASICA allows manual rejection of components (e.g., based on visual inspection) to ensure consistent application of the algorithm any ICs identified as artifacts were automatically removed from the data. According to Krug and Gramman (2020), participant movement in mobile EEG experiments has been shown to result in fewer brain-related Independent Components (ICs) (ICs remaining) as there are more muscle-related ICs (ICs removed) in the data. However, the ICA decomposition method is still a powerful tool for cleaning EEG data. Table 3.2 indicates the number of ICs removed for each participant (from a total of 30 ICs). Each IC is characterized by a topography, which reflects the projection of the independent source onto the scalp electrodes. The ICs can be treated as single independent sources because they are linear combinations of the original electrode signal (Chaumon, Bishop & Busch, 2015), meaning that the total number of ICs is limited by the total number of recording electrodes. Thus, in our study, we used 30 electrodes to capture EEG signals leading to a total of 30 ICs. Although there is some variability in the total number of ICs rejected, as exhibited in Table 3.2 the SASICA method consistently detected artifactual components.

Table 3.2 Independent Components rejected through the automatic selection and identification process of SASICA algorithm

Participant:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ICs rejected:	24	23	25	21	21	19	26	23	24	26	20	22	20	19	24

To explore the spectral dynamics of the data over time, a time-frequency analysis was performed through the convolution of Morlet wavelets (9 cycles at the lowest frequency and a maximum of 32 cycles at 40Hz for the highest frequency) across the epoch. Event-Related Spectral Perturbations (ERSP) were computed by dividing the power during the period of interest (-3000ms to 0) by the power during the baseline period (-5000ms to -4000ms) on a single trial basis (the choice of baseline is discussed in detail below). The ERSP measures average dynamic changes in the amplitude of any given ongoing EEG frequency as a function of time (relative to the experimental event of interest – in this case, the trigger pull). To investigate neural activity prior to the initiation of the trigger pull, EEG data were examined in the last 3 seconds prior to the trigger pull). This 3 second epoch window was selected to match the most used epoch in previous studies examining shooting performance (cf. Table 3.1; see Del Percio *et al.,* 2009; Doppelmayr, Finkenzeller & Sauseng, 2008; Loze *et al.,* 2001), allowing comparisons between the current findings and those reported in the existing literature.

Baseline correction methods are commonly used in the wider EEG literature across both frequency and ERP analyses. The baseline correction method is particularly important in the frequency domain, where it has the advantage of reducing overall scaling differences between the frequencies, which is believed to make them more comparable (Roach & Mathalon, 2008). As mentioned earlier in this Chapter, the baseline correction process is sometimes stated in the sporting literature, but in many studies it simply is not mentioned. Here, following best practice in the wider literature, we choose to investigate the changes in neural activity underlying successful and unsuccessful performance relative to a baseline. Consequently, the baseline period chosen for this study was -5000ms to -4000ms prior to the trigger pull (cf. Del Percio *et al.,* 2009; Bertollo *et al.,* 2016).

3.7 Data Analyses

Power relative to baseline values expressed as a percentage change (in %) were compared over time, between conditions, across *a-priori* defined frequency bands (Theta 4-7 Hz; Alpha 8-12 Hz; SMR 13-15 Hz; Beta 15-30 Hz) at each electrode site. Data from each frequency band was analysed independently using a within-subject repeated measures ANOVA (2 x 3 x 4 x 3) with factors of Performance (successful/unsuccessful), Time(T1/T2/T3), Region (Frontal/Central/Parietal/Occipital) and Electrodes (F3/Fz/F4; C3/Cz/C4; P3/Pz/P4; O1/Oz/O2) in line with Del Percio et al., (2009). Given the focus on examining the effects of performance, any significant interactions involving performance were followed up by ANOVAs examining the pattern of effects over time, or between electrodes (e.g., examining each time window using ANOVA with factors of Performance and Region or Electrode as appropriate). All analyses were carried out using a significance threshold of $p<0.05$, and any significant effects involving performance were followed up using paired sample t-tests (including Bonferroni correction for multiple comparisons where appropriate) to confirm whether performance related differences were reliable. Finally, to assess data quality and the choice of baseline period we examined variability in the baseline via the Root Mean Square (RMS, i.e., the arithmetic mean of the squares of a set of values). RMS was calculated independently for successful versus unsuccessful shots, across the entire baseline period, to determine any deviation in signal quality across conditions that might affect the interpretation of the results in the specific frequency bands. RMS was applied to all electrodes chosen to be analysed in this study, and examined for each participant individually, to provide insight into the overall quality of the EEG recording.

3.8 Results

3.8.1 Behavioural Performance

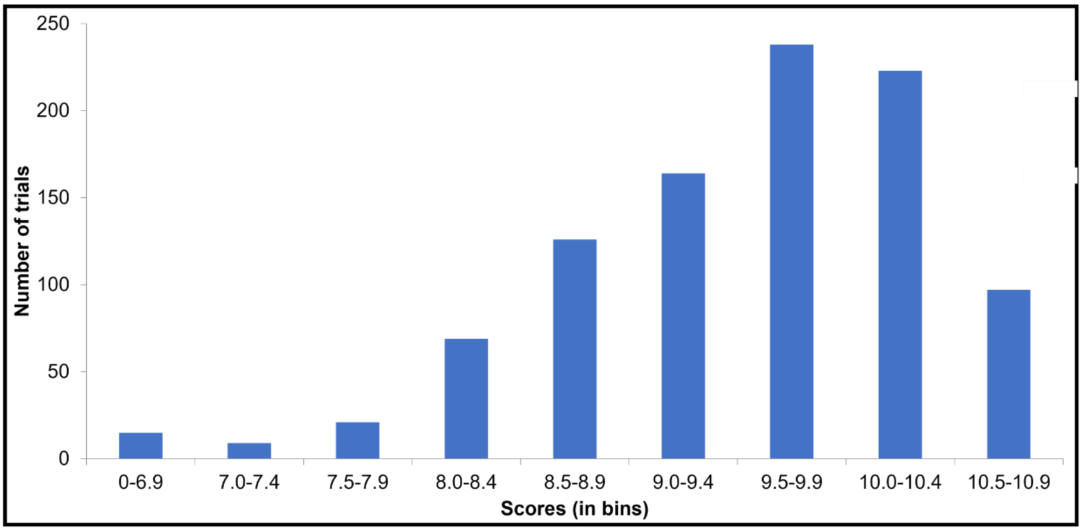


Figure 3.1. Frequency distribution graph including the scores from all participants. The grand mean is 9.4 and successful performance scores are above 9.4 and unsuccessful below 9.4.

Figure 3.1 exhibits a frequency distribution outlining the number of trials across a range of scoring bins for all 15 participants. Based on the grand average mean successful performance scores range from 9.4 and above. Table 3.3 below exhibits the mean, standard deviation, maximum and minimum values of each participant individually. Examination of the data led to Participant 7 being removed from further processing and analysis because they are a clear outlier, with a minimum score of 0 and a mean of 8 compared to all other participants.

Table 3.3 Mean, Standard deviation, Maximum and Minimum Scores for each individual participant.

Participant	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Mean	9.4	9.2	9.4	9.8	9.6	9.3	8.0	9.4	9.4	9.3	9.8	9.6	9.6	9.4	9.8
S.D.	0.8	0.8	0.6	0.5	0.7	0.8	1.7	0.9	0.7	0.8	0.6	0.8	0.6	0.8	0.6
Maximum	10.6	10.9	10.7	10.7	10.8	10.8	10.6	10.8	10.8	10.9	10.7	10.8	10.7	10.6	10.8
Minimum	7.9	6.6	8.1	8.5	7.6	7.3	0	6.9	8	7.3	8.3	7.5	8.1	7.3	8.7

Following the removal of Participant 7 the new grand average mean was 9.5. Thus, in our EEG analysis we have classified successful trials as shots scoring 9.5 and above, and unsuccessful trials as those scoring 9.4 and below. Table 3.4 highlights the total number of trials that survived the EEG analysis. As can be seen in Table 3.4, for some individuals the trial numbers included for each condition could be regarded as being low. In the prior sports literature, however, Loze *et al.,* (2001) performed analysis on the 5 best and 5 worst trials from each individual participant (N=6) which would then result in 30 trials in total for each condition (successful/unsuccessful). By contrast, the minimal number of trials per condition in the current study was 11(Participant 4, successful shots) and all analyses are based on a total of 467 successful and 312 unsuccessful trials.

Table 3.4 Total of successful and unsuccessful trials surviving EEG analysis.

Participant	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Successful	57	48	24	11	38	32	41	35	41	31	41	25	28	15
Unsuccessful	15	25	28	40	29	27	13	21	15	22	12	27	26	12

3.8.2 Time-Frequency analysis

To provide an overview of changes in EEG power throughout the pre-shot period a series of time-frequency plots were generated, characterising the pattern of effects for successful and unsuccessful performance. Individual time-frequency plots are presented for frontal, central, parietal and occipital regions to illustrate how variable the pattern of activity is across the scalp. Before presenting the outcomes of statistical analysis focused on each frequency band, we first describe the pattern of effects that is shown in the time-frequency plots.

Frontal Region

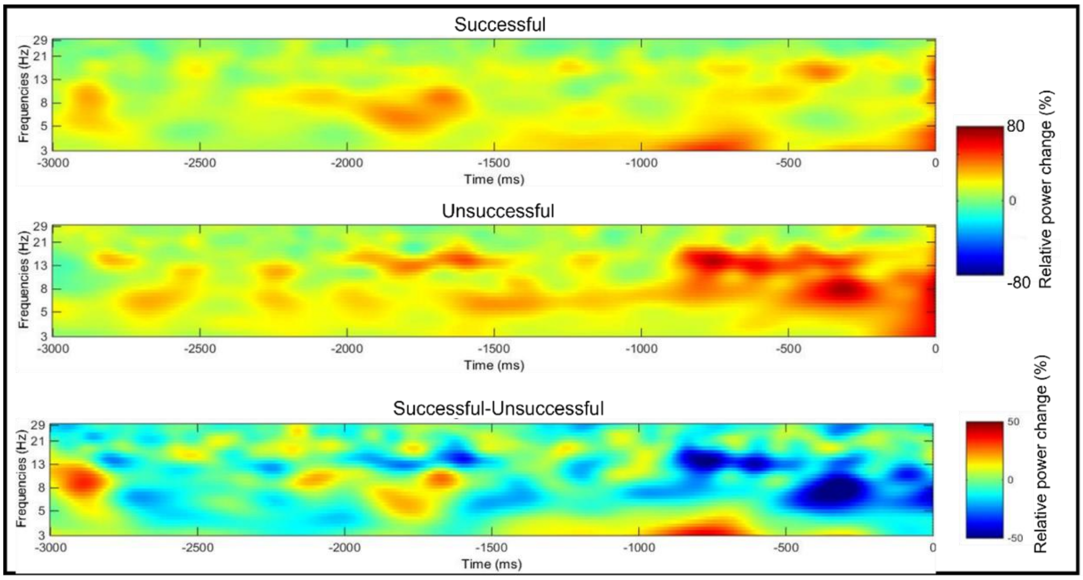


Figure 3.2. The time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the frontal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Figure 3.2 illustrates changes in power across all frequency bands for successful compared to unsuccessful performance over the pre-shot period, averaged across a set of frontal electrodes (F3/Fz/F4). The first two windows (-3000ms to 2000ms and -2000ms to -1000ms) exhibit a short-lived increase in theta (4-7 Hz) and alpha (8-12 Hz) for successful performance. By contrast, during the third time window (-1000ms to 0ms) there appears to be a stronger and longer lasting increase in power for unsuccessful performance, initially exhibited in the SMR band (13-15 Hz), followed by a clear peak in alpha (8-12 Hz) and theta (4-7 Hz) power – an effect that is particularly pronounced during the final 500ms before the shot.

Central Region

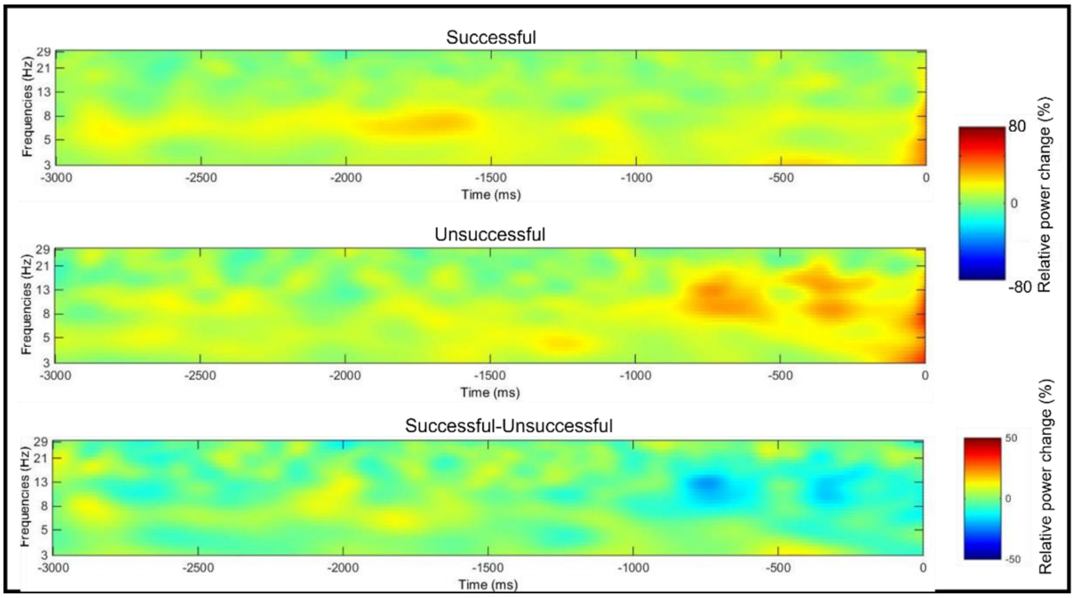


Figure 3.3. The time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the central region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Figure 3.3 illustrates changes in power across all frequency bands averaged across a set of central electrodes (C3/Cz/C4). In comparison to the effects seen over frontal electrodes there is far less activity throughout the pre-shot period over central electrodes. During the second time window (-2000ms to -1000ms) there appears to be a short-lived increase in theta (4-7 Hz) for successful performance. By contrast, during the third time window (-1000ms to 0ms) there appears to be a stronger and longer lasting increase in activity for unsuccessful performance, exhibited in both the SMR (13-15 Hz) and alpha (8-12 Hz) bands. As is evident in the difference plot, however, the increases underlying unsuccessful compared to successful performance are relatively short lived within time window 3.

Parietal Region

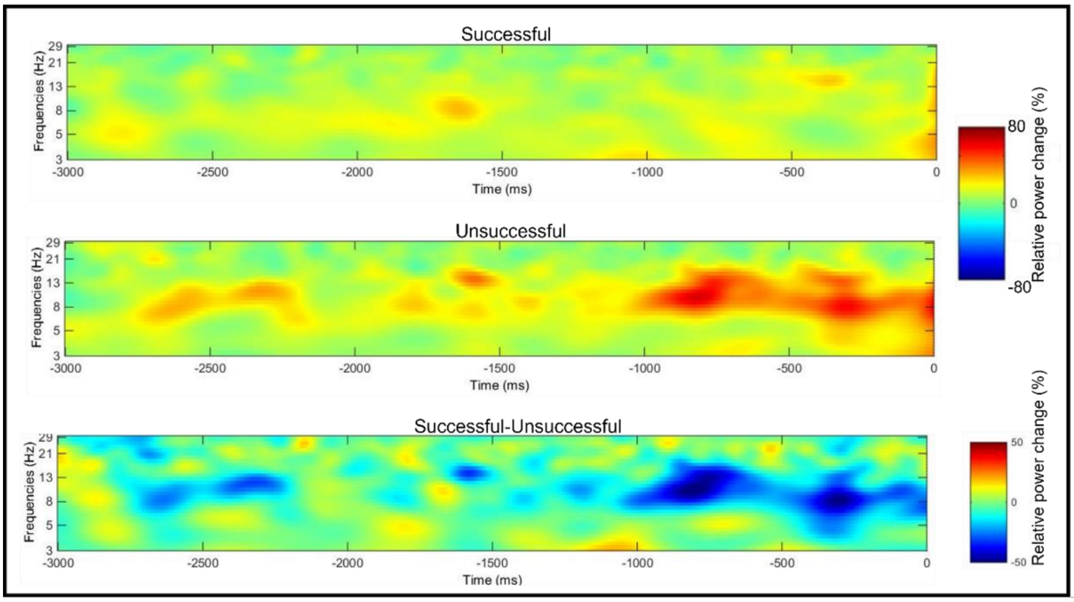


Figure 3.4. The time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Figure 3.4 illustrates changes in activity averaged across a set of parietal electrodes (P3/PZ/P4). Whilst there is little sign of changes in activity for successful performance, large increases in activity are present for unsuccessful performance. An increase in alpha activity (8-12 Hz) can be seen underlying unsuccessful performance during time window 1, an effect that becomes stronger and longer lasting during time window 3, extending into the SMR (13-15 Hz) and theta (4-7Hz) bands during the final 500ms before the shot. This pattern of effects is mirrored in the difference plot, reflecting the absence of effects for successful performance.

Occipital Region

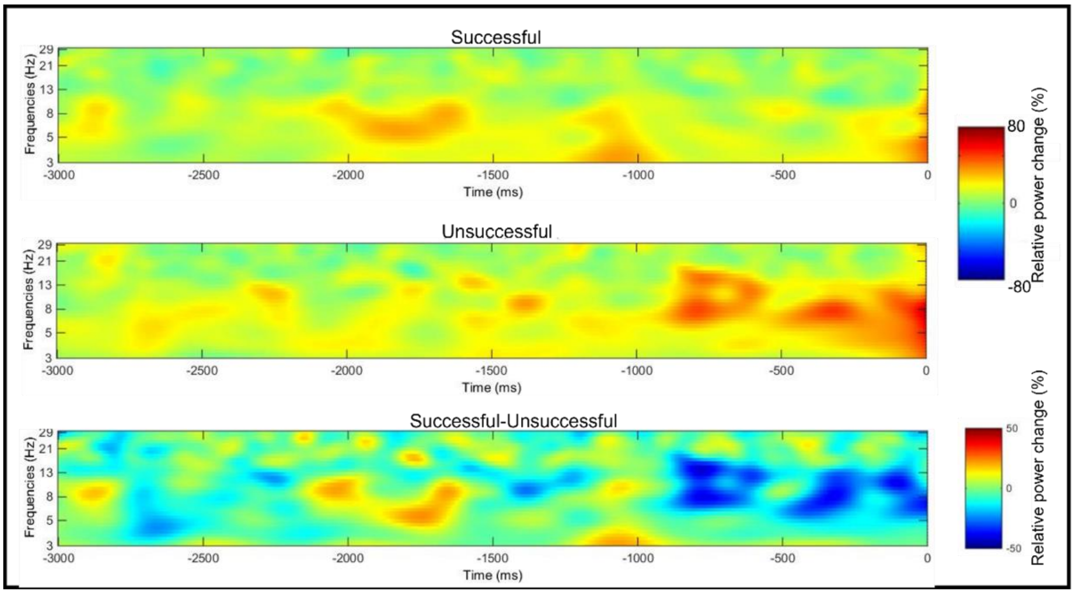


Figure 3.5. The time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the occipital region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Figure 3.5 illustrates the pattern of activity at occipital electrodes (O1/Oz/O2). Whilst successful performance is associated with a short-lived increase in theta (4-7 Hz) during time window 2, unsuccessful performance exhibits clear increases in alpha during time window 3, extending into the SMR (13-15 Hz) and theta (4-7 Hz) bands during the final 500ms. As was the case at parietal electrodes, the increase in activity for unsuccessful performance is mirrored in the difference plot, reflecting the absence of effects for the successful performance.

Taken together, the time-frequency plots suggest that there are marked changes in brain activity for both successful and unsuccessful performance. Two consistent patterns are clear in the data. First, many of the effects appear to be relatively short-lived, with brief bursts of activity (particularly alpha) present throughout the pre-shot period. Second, the strongest effects appear to be present during the final second before the shot, when the largest increases in activity are seen for unsuccessful shots. However, even during the final second the effects are relatively short-lived, extending into the SMR (13-15 Hz) band initially and then into alpha (8-12Hz) during the final 500ms. Nonetheless, as planned, below the data are analysed using the 1 second time windows typically reported in the prior literature.

3.8.2.1 Alpha (8-12 Hz)

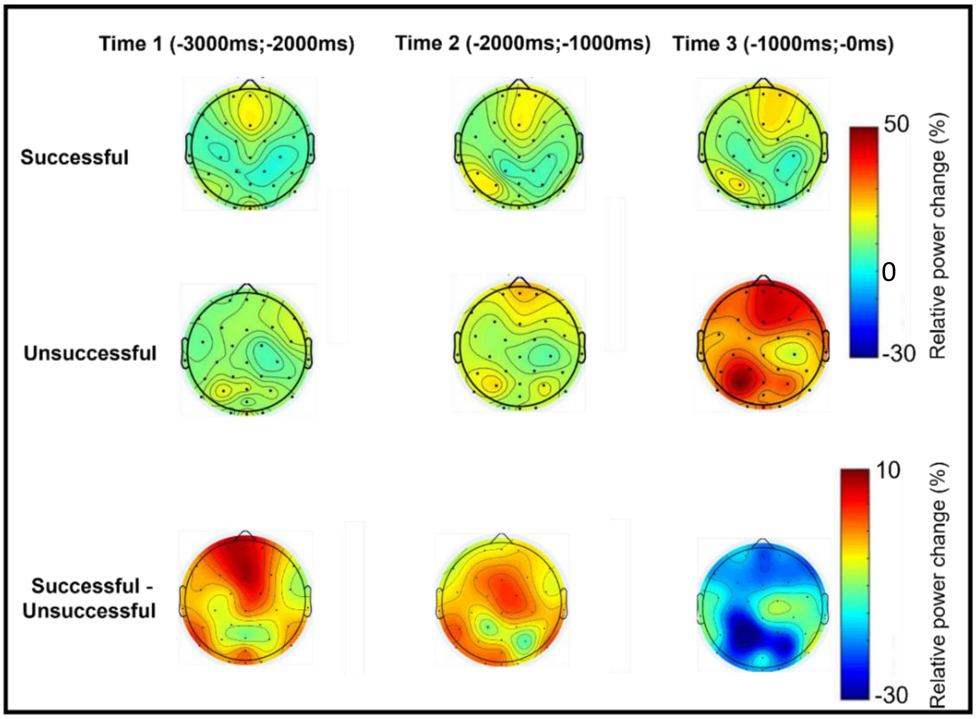


Figure 3.6. Topographical maps representing alpha activity (8-12Hz) for successful and unsuccessful performance over the three-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 3.6, there is a clear pattern of increases in alpha power observed for both successful and unsuccessful performance compared to the baseline. A larger increase in alpha is evident for unsuccessful performance overall across all time windows. The effect becomes larger and more focused particularly over frontal and parietal electrodes during time window 3 for unsuccessful performance. The changing pattern of effects is illustrated in the difference maps (successful – unsuccessful): a decrease in alpha that is maximal over centro-parietal electrodes during time window 3 (see Figure 3.6).

Initial analysis of the data examined the overall pattern of effects using a repeated measures (2 x 3 x 4 x 3) ANOVA with factors of Performance (successful/unsuccessful),Time(T1/T2/T3),Region(Frontal/Central/Parietal/ Occipital) and Electrode (F3/Fz/F4; C3/Cz/C4; P3/Pz/P4; O1/Oz/O2). Analysis revealed an interaction between performance and time [F(2,26)=6.67,p< .05], confirming that the difference in alpha between successful and unsuccessful performance changes over time. Despite the impression provided in Figure 3.6, it is notable that the analysis did not reveal any significant interactions with region or electrode (all p's > 0.44). The significant interaction between performance and time is illustrated in Figure 3.7, collapsed across all electrodes. Whilst successful and unsuccessful shots were associated with similar levels of alpha during time window 1, unsuccessful performance exhibited a large increase in alpha during time window 3. Additional analysis was carried out to examine the change in alpha during each time window using paired-samples t-tests, revealing that there was no significant difference between successful and unsuccessful performance during time window 1 [t(13)=-.345,p=.735] or time window 2 [t(13)=-.430,p=.674]. Whilst the analysis provides some evidence of a significant difference during time window 3 [t(13)=-2.28,p=.040], the result does not survive a Bonferroni correction for multiple comparisons (which requires p<0.017 for significance).

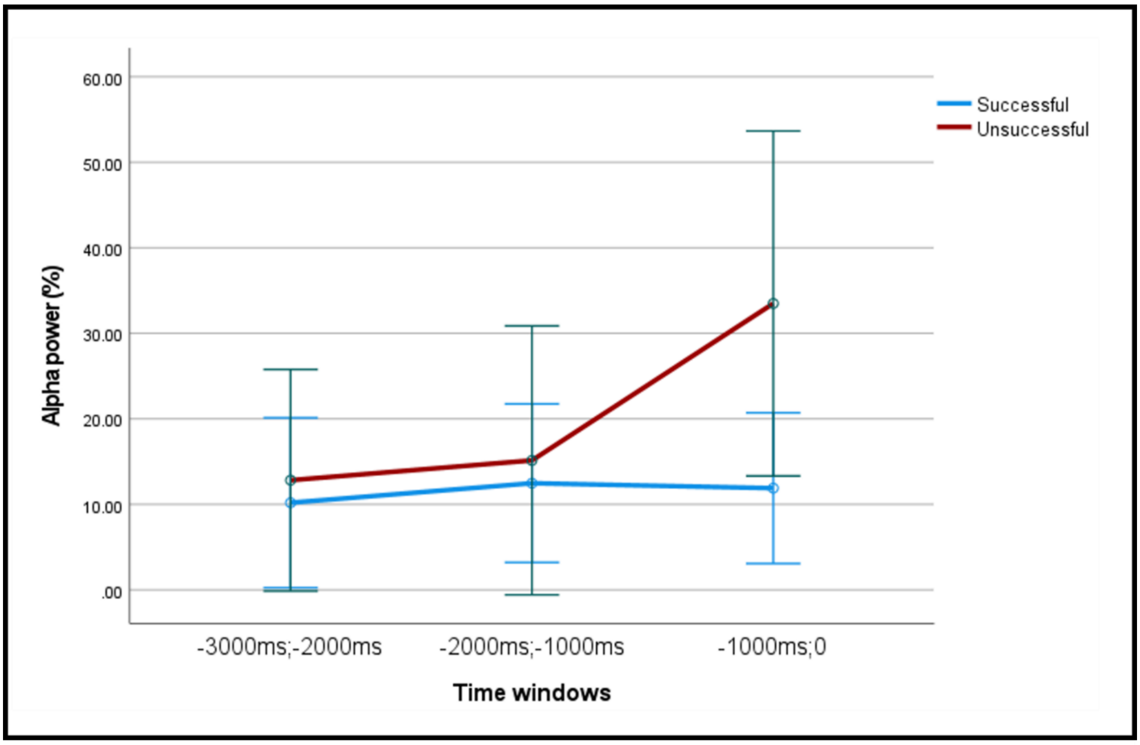


Figure 3.7. The figure exhibits the change of alpha power over time in successful and unsuccessful performance. As can be seen there is more alpha power underlying unsuccessful performance at the third time window compared to successful performance. Error bars represent the 95% confidence intervals.

3.8.2.2 Theta (4-7 Hz)

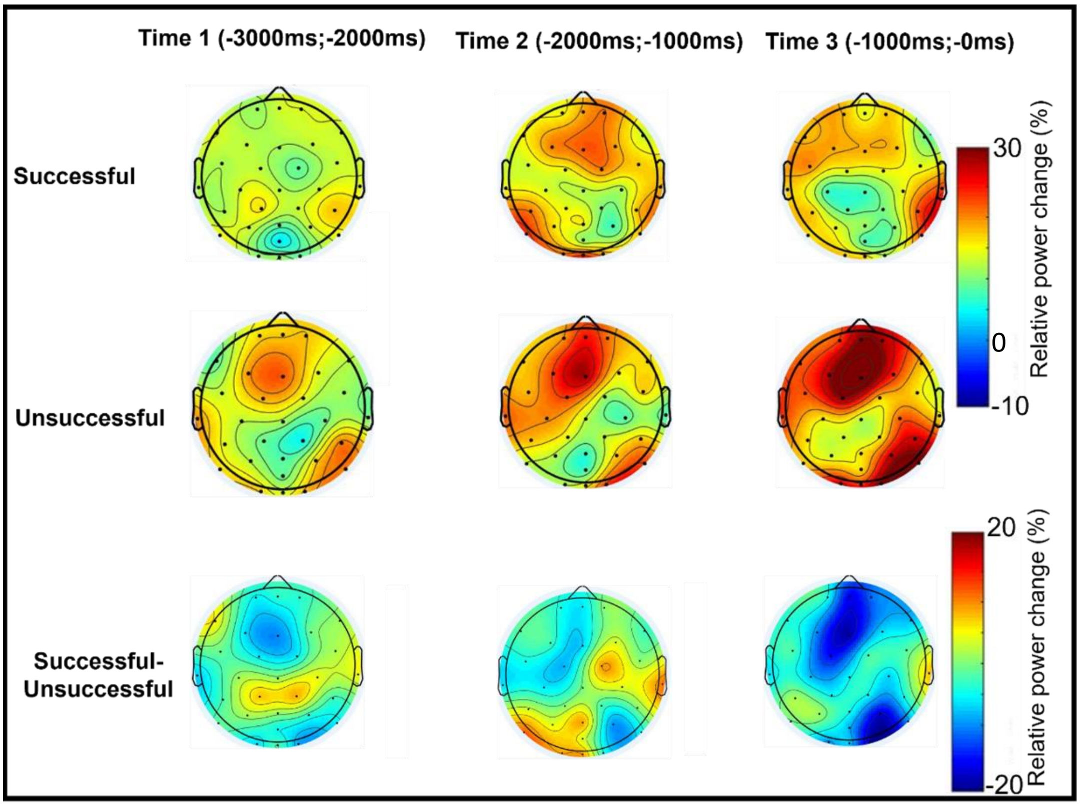


Figure 3.8. Topographical maps representing theta power (4-7 Hz) for successful and unsuccessful performance over the three-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represent the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 3.8 there seems to be an increase of theta activity underlying unsuccessful and successful performance compared to the baseline. The increase of theta is larger for unsuccessful performance and is evident as a maxima over frontal electrodes during all three time windows. Consistent with the impression provided by the time-frequency plots, the topographic maps suggest that the changes in theta are largest during the final second before the shot – reflected in the large negative peak over frontal electrodes in the difference map. Despite the fact that there appears to be clear differences in theta, analysis of the data using a repeated measures (2 x 3 x 4 x 3) ANOVA revealed no main effect of performance [F(1,13)=.600,p=.45], and no significant interactions between performance and the factors of time, region or electrode (all p's > .37). Contrary to the impression provided in Figure 3.8, therefore, it is notable that the analysis did not reveal any significant differences in theta activity between successful and unsuccessful performance.

3.8.2.3 Beta (15-30 Hz)

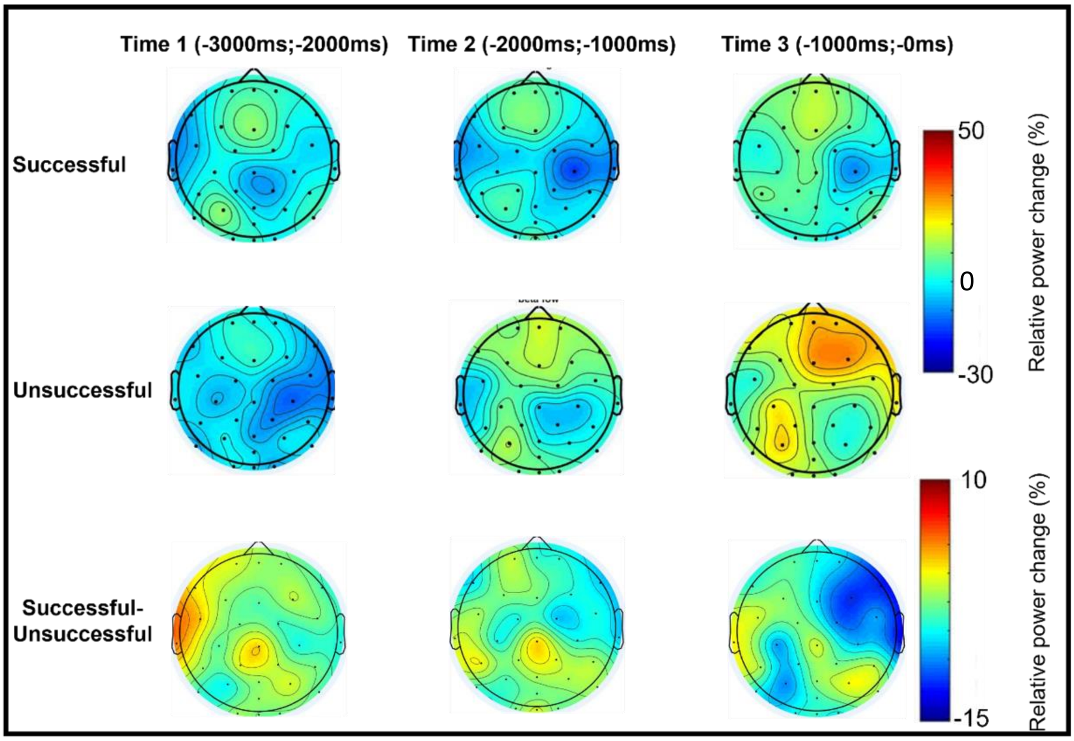


Figure 3.9. Topographical maps representing beta power(15-30Hz) for successful and unsuccessful performance over the three-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 3.9, the topographic maps suggest that there are changes in beta power underlying unsuccessful and successful performance. Unsuccessful shots are associated with a larger decrease in beta over right central electrodes during time window 1. During time windows 2 and 3 the effect of beta decrease is larger for successful shots compared to unsuccessful shots, with a larger decrease evident over right central electrodes for successful shots. Moreover, unsuccessful shots are associated with an increase in beta over frontal electrodes – a pattern that appears similar across all time windows and becomes maximal during time window 3. Even though there seems to be a difference in beta power, planned analysis of the data revealed no main effect of performance [F

(1,13) = .1.96, p = .18] and no significant interactions between performance and the factors of time, region or electrode (all p's > .26). As for theta, therefore, the analysis did not reveal any evidence for significant differences in beta power between successful and unsuccessful performance.

3.8.2.4 SMR (13-15 Hz)

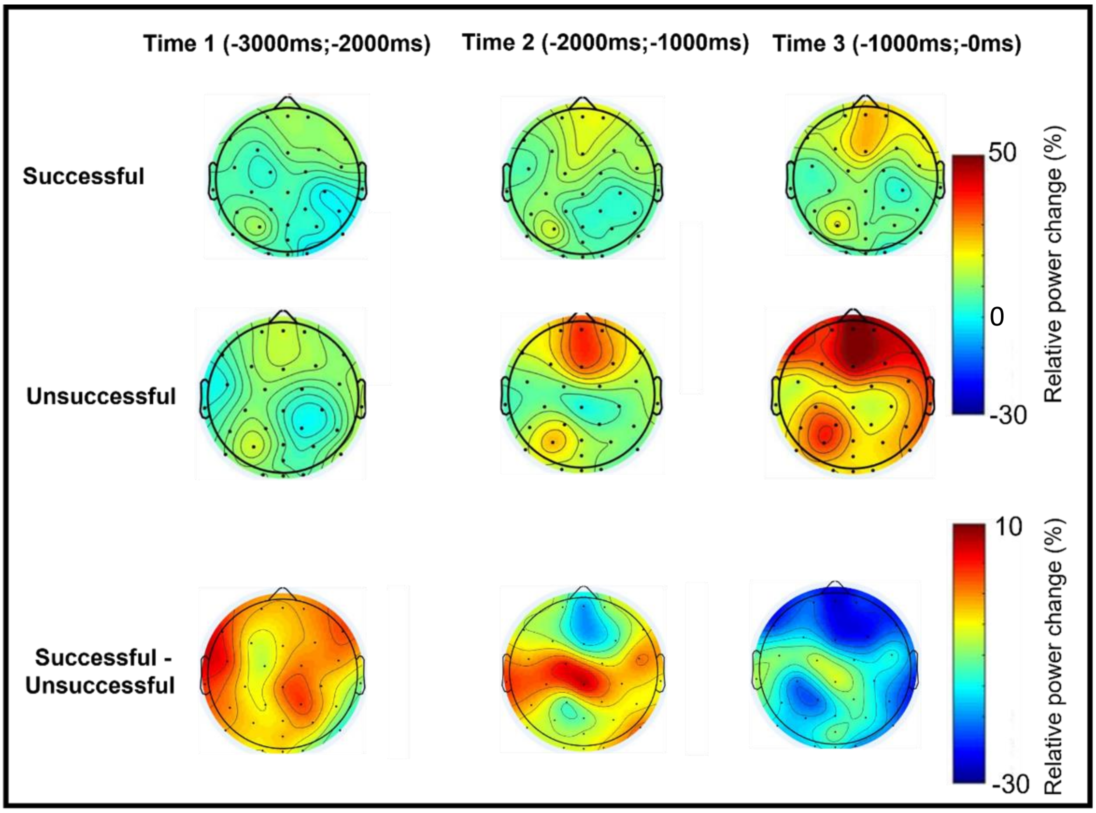


Figure 3.10. Topographical maps representing SMR power(13-15Hz) for successful and unsuccessful performance over the three-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 3.10 there appears to be an increase for SMR power underlying successful and unsuccessful performance, which becomes larger for unsuccessful performance, maximal over frontal electrodes during the second and third time windows. The change in SMR is clearly larger for unsuccessful shots during the later time windows compared to the baseline. Despite the impression provided by Figure 3.10, planned analysis of the data revealed no main effect of performance

[F(1,13)=2.55,p =.13] and no significant interactions involving performance and time, region or electrode (all p’s > .060). As for theta and beta, therefore, the analysis did not reveal any evidence for significant differences in SMR power between successful and unsuccessful performance.

3.8.3 Additional Targeted analysis

As no significant main effects or interactions have been revealed when the analysis followed the approach provided in the literature, follow up analysis was employed to better target the data driven pattern of effects. These additional analyses were informed by the pattern of effects reported in the existing literature and the following sections will provide outcomes from statistical analysis focusing on each band and targeted electrodes. To increase the likelihood of capturing the effects that are visible in the time frequency plots (where the effects are often relatively short lived) the targeted analysis employed shorter 500ms time windows and focused on the electrode locations where the effects were most prominent. In all cases, however, the analysis was carried out using the standard frequency bands examined above.

3.8.3.1 Alpha (8-12 Hz)

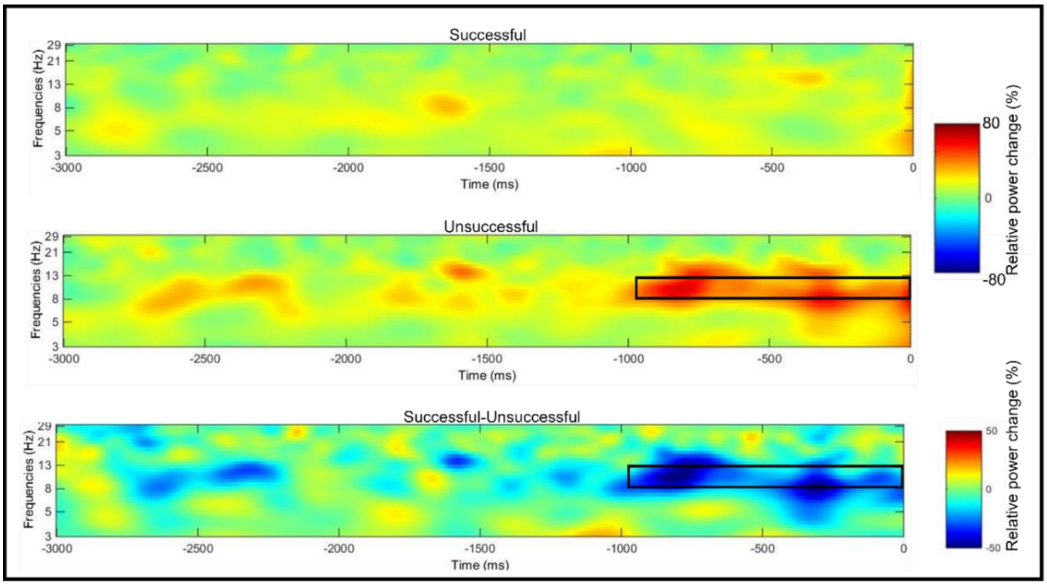


Figure 3.11. The time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease. The black box represents the maximal difference between the two levels of performance within the alpha power (8-12 Hz).

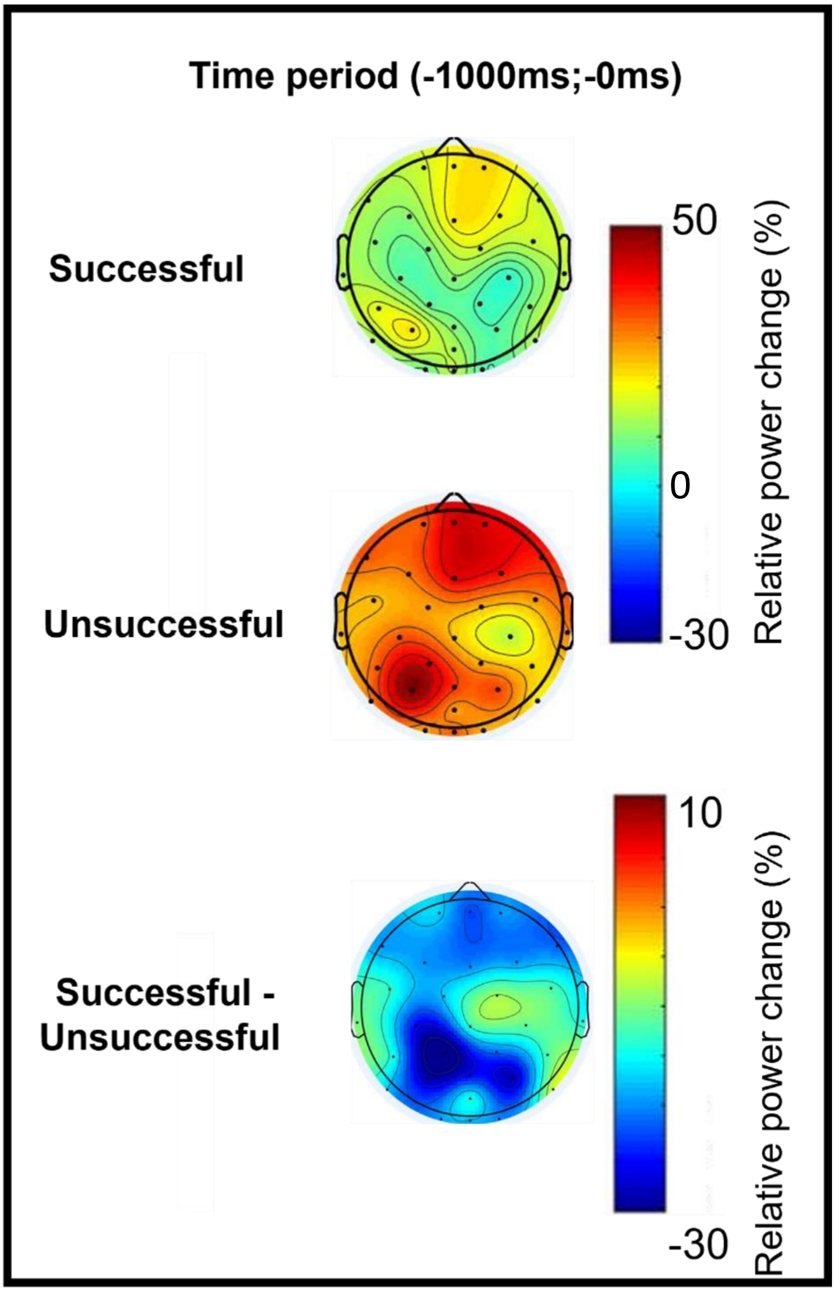


Figure 3.12. The topographical maps exhibit successful and unsuccessful performance for alpha power (8-12 Hz) at time window (-1000ms;0ms). The difference topographical maps exhibit the difference between successful – unsuccessful performance. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As seen in Figure 3.11 and 3.12 there is an increase of alpha (8-12Hz) power compared to the baseline characterizing both successful and unsuccessful performance. This increase is higher in unsuccessful performance over frontal and especially parietal areas during the last second before the trigger pull. Del Percio *et al.,* (2009) reported a significant difference between high and low performance within low alpha frequency (8-10 Hz) at electrode P4. In line with the reported difference and pattern of activity exhibited at parietal electrodes, a 2 x 2 x 3 ANOVA was performed with factors of Performance (successful/unsuccessful), Time (T3a[-1000ms;-500ms]/T3b[-500ms;0]) and Electrode (P3/Pz/P4). A significant main effect of performance was revealed [F(1,13)=6.21,p=.02]. Unsuccessful performance (M=41.55%) was characterized by more alpha power in contrast to successful (M=13.04%) performance. The exhibited result is in line with the pattern of activity exhibited in Figures 3.11 and 3.12 with more alpha power underlying unsuccessful performance during the last second prior to the trigger pull.

Additionally, correlational analysis has been performed-on the single trials of participants-to further examine the pattern of results. Correlational analyses were performed on all single trials, focusing on the last second time window for parietal (P3/Pz/P4) alpha in line with the significant results exhibited from the ANOVA. A significant weak negative correlation was found between parietal alpha power and performance, meaning that the less alpha power, the higher the shooting performance [r (779)= -0.07, p =0.04]. The results from the correlational analysis confirm the pattern of results exhibited in Figure 3.11 and 3.12 with less alpha power underlying successful performance.

3.8.3.1.1 Theta (4-7 Hz)

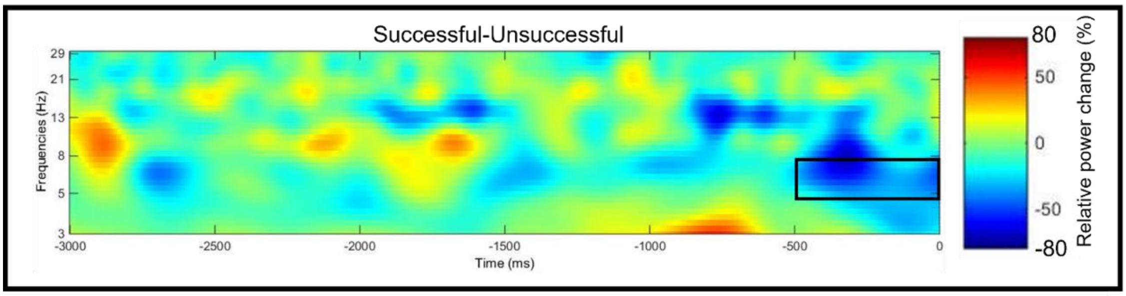


Figure 3.13. The difference time frequency plots exhibit the neural activity across frequencies in the 3 second period of interest at the FZ electrode. Zero indicates the time of the trigger pull. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease. The black box presents the maximal difference between the two levels of performance within the theta power (4-7 Hz).

As seen in Figure 3.13, there is a difference in theta power between successful and unsuccessful shots during the last 500ms before trigger pull. The topographical scalp maps (Figure 3.14) shows that this difference is focal over mid-frontal areas (mainly electrode Fz) and it reflects an increase of theta power, which is only present before unsuccessful shots. In line with the topographic maps (Figure 3.8) there is an increase of theta power which is maximal over the Fz electrode during the last time window (-1000ms;0). In line with previous literature (e.g., Doppelmayr, Finkenzeller, & Sauseng, 2008) and the pattern of results exhibited in Figure 3.13 and 3.14, a repeated measures 2x2 ANOVA was performed with factors of Performance (successful/unsuccessful) and Time (T3a[-1000ms;-500ms]/T3b[-500ms;0]). A significant interaction was revealed between performance and time [F(1,13)=4.91,p=.04]. A paired-samples t-test was performed to compare the two levels of performance within each time window. After Bonferroni correction for multiple comparisons (p=0.02), a significant difference was revealed within the final time window (-500ms;0), [t(13)=-3.27,p=.006]. Unsuccessful performance (M=44.89%) was associated with more theta power compared to successful (M=12.20%) performance, in line with the pattern of activity exhibited in Figures 3.13 and 3.14 (at the Fz electrode).

Additionally, correlational analyses have been performed-on the single trials of participants-to further examine the pattern of results. Correlational analyses were performed on all single trials within the 500 ms time window for frontal midline (Fz) theta power in line with the significant results exhibited from the ANOVA. A significant weak negative correlation was found between frontal midline theta power and performance, meaning that more theta power, the lower the shooting performance [r (779)= -0.08, p =0.02]. The results from the correlation confirm the pattern of results shown in Figure 3.13 and 3.14, with less theta power underlying successful performance at electrode Fz.

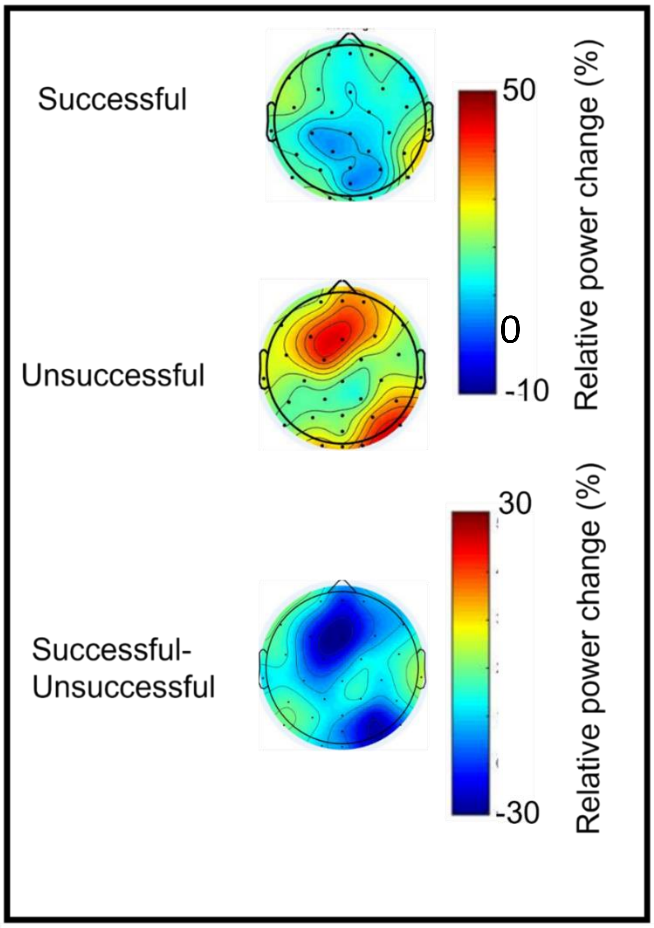


Figure 3.14. The topographical scalp maps exhibit successful and unsuccessful performance at time window -500ms to 0ms within the theta frequency range (4-7 Hz). The difference topographical map exhibits the difference between successful-unsuccessful performance. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

3.8.3.1.2 Beta (15-20 Hz)

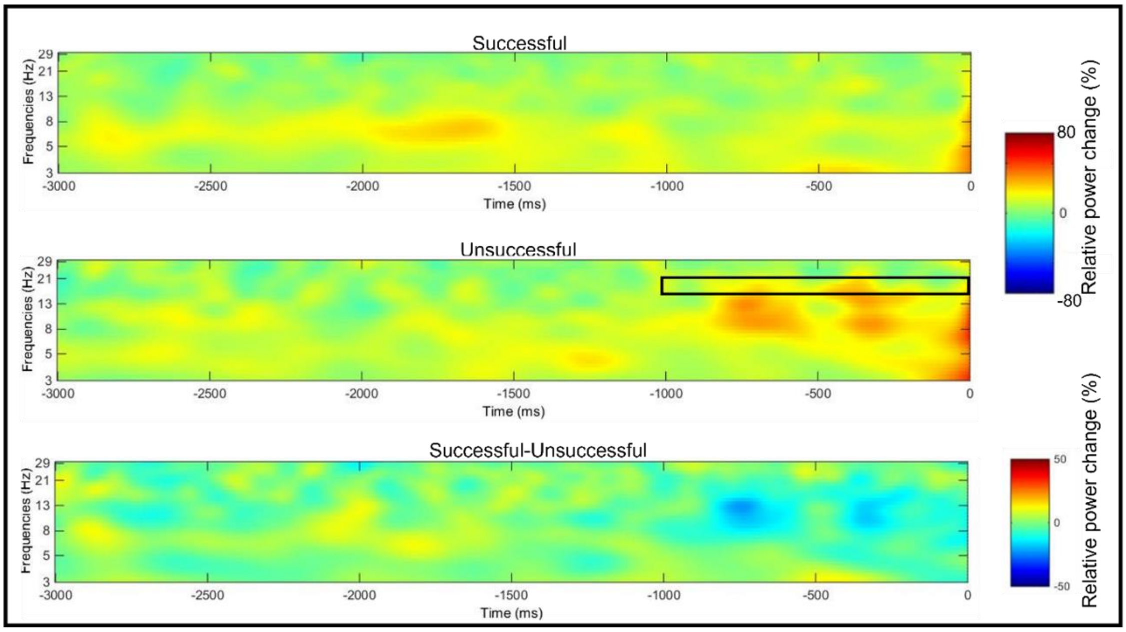


Figure 3.15. The time frequency plots exhibit the neural activity across the frequencies in the 3 second period of interest at the central region. Zero indicates the time of the trigger pull. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful-unsuccessful. The scaling represent the relative power change (%) from baseline, with red indicating an increase and blue a decrease in power. The black box presents an increase of beta power (15-20 Hz) underlying unsuccessful performance.

Figure 3.15 exhibits the time frequency plots at the central region. The black box presents an increase of beta power characterizing unsuccessful performance. As exhibited in the time frequency plot, the pattern of activity within the beta frequency range is limited to 15-20 Hz (in comparison to our initial analysis, which focused on a wider beta range from 15 to 30Hz). A repeated measures 2 x 2 x 3 ANOVA was performed with factors of Performance (successful/unsuccessful), Time (T3a[-1000ms;0-500ms]/T3b[-500ms;0]) and Electrode (C3/Cz/C4). A significant main effect of performance was revealed [F(1,13)=5.57,p=.03]. In line with previous reported results within the alpha and theta frequency, more beta power characterizes unsuccessful (M=17.46%) performance compared to successful (M=6.35%) performance.

Further examination of the pattern of activity was performed with the use of correlational analysis. Correlational analysis was performed on all single trials within the last second time window for beta power (15-20 Hz) within the central region in line with the significant results exhibited from the ANOVA. The results failed to reach statistical significance for beta power [r(779)= -0.20, p =0.57].

3.8.3.1.3 SMR (13-15 Hz)

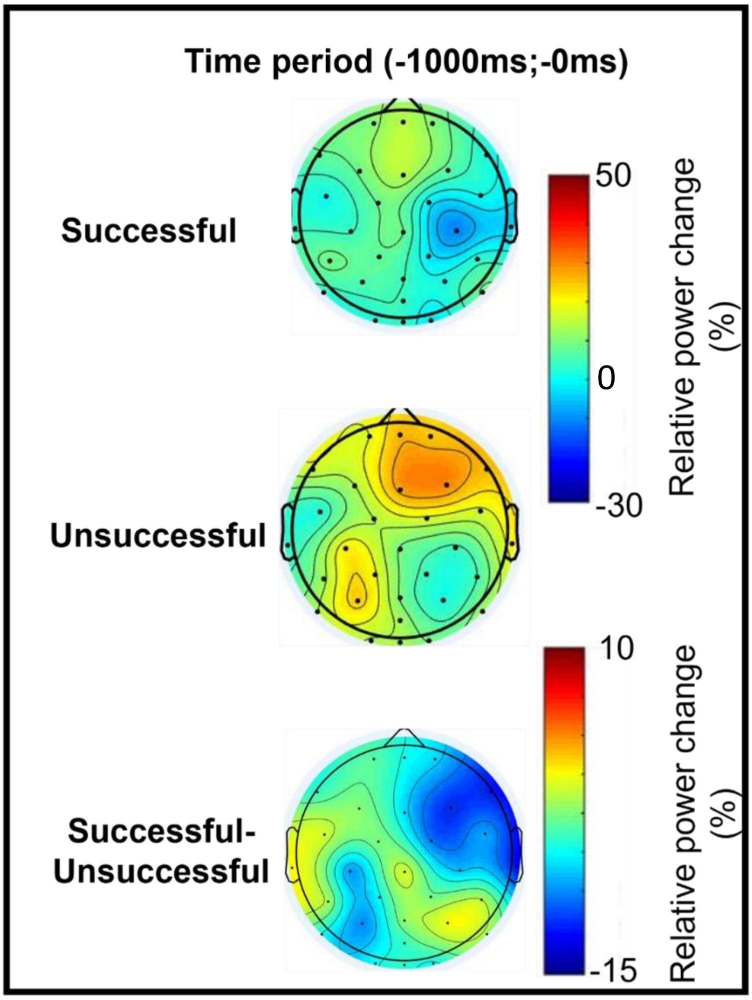


Figure 3.16. The topographical scalp maps exhibit successful and unsuccessful performance at time window -1000ms to 0ms within the SMR frequency range (13-15Hz). The difference topographical map exhibits the difference between successful-unsuccessful performance. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As exhibited in Figure 3.16 changes in SMR power over central areas are present for both successful and unsuccessful performance, with a larger increase of SMR power compared to the baseline evident for unsuccessful performance. In line with previous literature (e.g., Cheng *et al.,* 2017) SMR was examined at the central (C3/Cz/C4) region. A repeated measures 2 x 2 x 3 ANOVA was performed with factors of Performance (successful/unsuccessful), Time (T3a[-1000ms;-500ms]/T3b[-500ms;0]) and Electrode (C3/Cz/C4). A main effect of performance was exhibited [F(1,13)=5.62,p=.034] with more SMR power underlying unsuccessful compared to successful performance. Additionally, a significant interaction between performance and electrode [F(2,26)=4.13,p=.028] was identified. Paired sample t-tests were performed to examine the significant interaction and after the Bonferroni correction a significant difference between performance (successful versus unsuccessful) was exhibited at C3 electrode [t(13)=-3.25,p=.006] with more SMR power underlying unsuccessful (M=28.85%) compared to successful (M=7.49%) performance.

Further examination of the pattern of activity was performed with the use of correlational analyses, performed on all single trials within the last second time window for SMR power within the central region. The results exhibit a negative correlation for SMR power and performance [r(779)= -0.15, p < .001]. The results confirm the pattern of activity exhibited within the ANOVA and Figure 3.16 with less SMR power underlying successful performance. Additionally, ANOVA revealed an interaction between performance and electrode. Paired-samples t-test revealed a significant difference in performance at electrode C3. Further correlational analysis was performed to examine the pattern of activity at the C3 electrode for SMR power but the analysis failed to reach statistical significance [r(779) = -.07, p =0.10].

3.8.4 Root Mean Square (RMS)

One of the aims of this study was to explore whether the differences in neural activity underlying successful and unsuccessful performance are due to the selection of the baseline period. Previous literature has not reported an examination of the baseline period activity. Consequently, the effects suggested in the literature could be driven by methodological artifacts or they could reflect genuine neural differences underlying successful and unsuccessful performance. The selection of the baseline activity (if selected) is based upon visual inspection of the EEG data, with researchers identifying that the period between -5000ms to -4000ms is typically free of artifacts compared to a period prior to that such as -6000ms to -5000ms. As a check on the suitability of this choice of baseline period here we examine variability in the baseline period using the Root-Mean-Square measure. In the wider EEG literature RMS is considered to be a useful measure to explore noise in the baseline, (Kappenman & Luck, 2010) and within the frame of this PhD this measure it is used to compare the amount of noise across recording conditions to establish the impact of residual noise on the period of interest examined.

3.8.4.1 Estimation of baseline residual noise

Figures 3.17, 3.18 and 3.19 exhibit the RMS in the baseline period activity at frontal, central and parietal regions, respectively, for each individual participant.

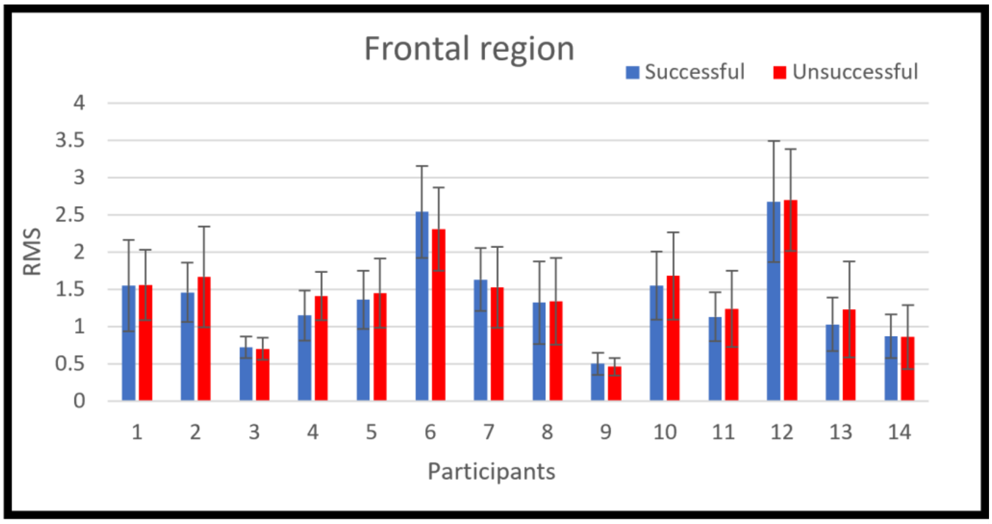


Figure 3.17. Root Mean Square (RMS) of the baseline period activity (-5000ms to -4000ms) recorded at frontal region across participants for successful (blue) and unsuccessful (red) performance.

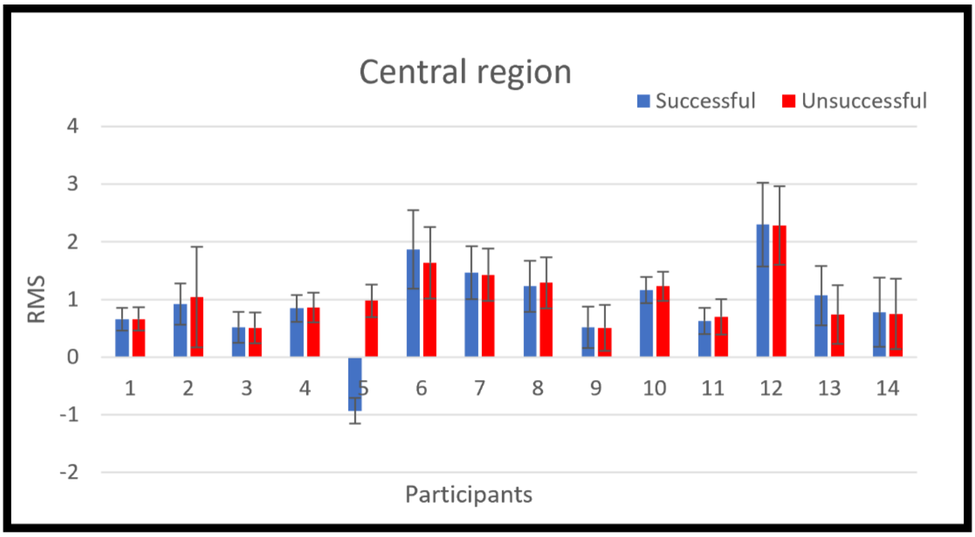


Figure 3.18. Root Mean Square (RMS) of the baseline period activity (-5000ms to -4000ms) recorded at central region across participants for successful (blue) and unsuccessful (red) performance.

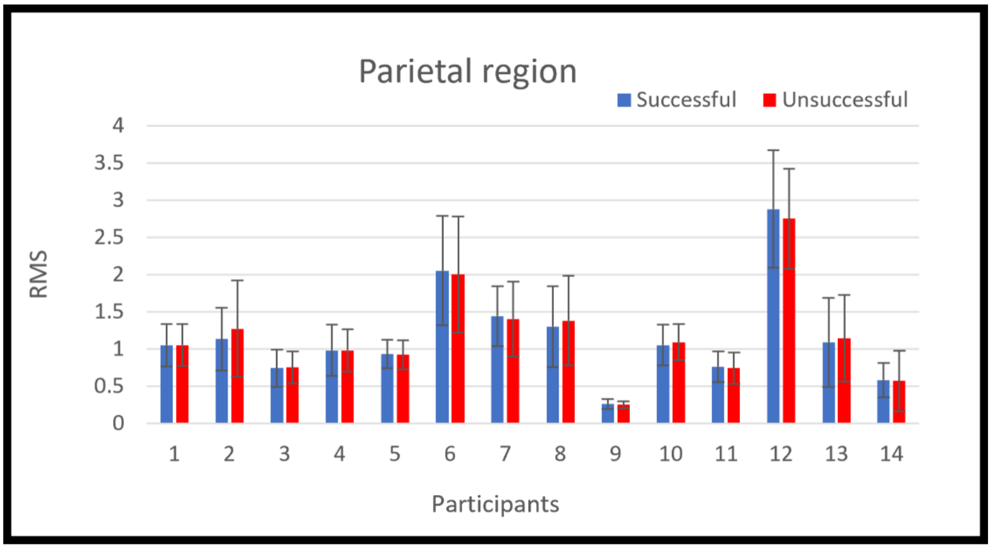


Figure 3.19. Root Mean Square (RMS) of the baseline period activity (-5000ms to -4000ms) recorded at parietal region across participants for successful (blue) and unsuccessful (red) performance.

As seen in Figures 3.17 to 3.19, no significant differences can be detected overall across regions and participants between successful and unsuccessful performance in the baseline period. The Figures highlight that just one participant (P5) appears to exhibit a difference, and only at the central region (Figure 3.18). Overall, however, the magnitude of activity associated with successful and unsuccessful performance does not appear to differ in the baseline period activity. Paired-samples t-test were performed for each region individually to examine if there were any reliable differences in the baseline period between successful and unsuccessful performance. There was no significant difference in the baseline period activity RMS at frontal electrodes between successful (M=1.39; SD=.61) and unsuccessful (M=1.43; SD=.58) performance [t(13)=-1.32,p=.20]. Similarly, there was no significant difference in the baseline period activity RMS at central electrodes between successful (M=0.93; SD=.74) and unsuccessful (M=1.04; SD=.49) performance [t(13)=-.79,p=.44]. And there was also no significant difference in the baseline period activity RMS at the parietal region between successful (M= 1.16, SD = .64) and unsuccessful (M=1.16; SD=.61) performance [t(13)=-.21,p=.83].

3.9 Discussion

The current study examined neural activity underlying successful versus unsuccessful shooting performance in an ecologically valid setting (a typical shooting range). We collaborated with athletes and coaches to develop an *in situ* representative shooting task that did not interfere with routine practice. We based our approach to EEG data analysis on the dominant approaches within the literature, characterising activity during a 3 second period leading up to the trigger pull, and independently examining distinct frequency bands. Whilst initial analysis revealed relatively little support for the claim that EEG signals might differ between successful and unsuccessful performance, targeted analyses confirmed that statistically reliable effects were present. To be clear, results revealed differences in the neural activity associated with successful and unsuccessful shots – EEG effects that were dissociable both temporally and topographically. Below we discuss the specific effects in detail, highlighting what the pattern of effects suggest about the cognitive basis of successful performance. We start, however, by discussing how the current study went beyond the gaps identified in the prior literature.

The first limitation identified was the fact that most shooting studies reported in the literature provide a comparison of the neural activity of experts versus novices. Although shooting related EEG research has provided insights into the neural mechanisms differentiating experts from novices, the results from these studies are not necessarily informative about the mechanisms underlying different levels of performance within experts (i.e., successful versus unsuccessful shots). Here we provide strong support for this claim. In broad terms, the present results demonstrate that the pattern of effects reported in studies comparing experts and novices is not the same as that found when comparing successful and unsuccessful shots. From a psychological perspective this suggests that researchers interested in understanding elite performance must examine behaviour within elite athletes. By extension, the present findings suggest that future studies must examine elite performers directly, by tracking changes in skilled behaviour over time (e.g., during development or following training interventions), or by investigating how performance varies under different conditions (e.g., during practice versus live competition). From an applied perspective it is important to understand how changes in the different frequency bands contribute to successful performance, so that coaches can use the information to produce better practice protocols (as well as monitoring and informing athletes about their performance).

The second limitation identified in the prior literature was the lack of ecological validity of the tasks employed – including studies that employed entirely non-sporting tasks (e.g., traditional cognitive paradigms). In Chapter 1 we described the issue of ecological validity in detail, highlighting the progress that has been made towards examining sporting behaviour. Even here, however, the majority of studies have employed adapted tasks that are not representative of real sporting behaviour. For example, studies have used a simulated shooting task that required participants to shoot towards a 4m target, (Haufler *et al.,* 2000). From the perspective of sports practitioners, adjusting the shooting target sacrifices much of the ecological validity of the task, as well as reducing the relevance of the findings (compared to if the recording was performed during actual performance). In the present case we chose pistol shooting because it is an ideal sport for use with EEG - due to the procedural routine of the task, the repetitive trials and the limited movement required to perform the trigger pull. Importantly, as highlighted in the results, collaboration with the athletes and coaches had two significant benefits. First, we were able to define successful performance in a manner that was meaningful to the athletes – based on the mean of all shots fired. Second, we were able to collect and analyse far more data than is typically reported – at least in part because we were not disrupting the athletes normal practice routine. Most importantly, perhaps, the current findings demonstrate that EEG can be used effectively *in situ,* building confidence in the mobile EEG approach for both researchers and sports practitioners alike.

The third limitation highlighted in our review of the literature was the different electrode locations chosen to examine neural activity. For example, previous studies have measured neural activity from a small number of recording sites (e.g., Loze *et al.,* 2001, employed 3 electrodes: T3/T4/OZ). By contrast, more recent studies such as Del Percio *et al.,* (2009) employed a 56-channel montage. This variability in the montage employed across studies has led to inconsistencies in the reported location of effects. To address this issue in the current study we used a standard 32-electrode montage (based on the International 10-20 system, Jasper, 1958) to acquire EEG data. Although this approach provided good coverage across the entire scalp, analysis of the data was focused on key regions of interest across frontal, central, parietal, and occipital regions. Moreover, given that the initial global analyses provided little evidence for reliable effects, the targeted analysis that followed was focused on a small number of electrodes. We note, however, that the present findings suggest broad coverage of the scalp is important, because of the variable locations at which EEG effects are present. Put simply, the current findings suggest that studies employing only a small number of electrodes are unable to capture all of the different EEG effects that are present.

The fourth limitation we focused on is the fact that most prior studies have only examined a single frequency band - typically alpha. By contrast, in the present study we examined a set of frequency bands, each of which had been identified as a candidate EEG effect in a prior study. Our ability to adopt this approach clearly depended on the aforementioned use of a whole-head montage. Importantly, this allowed us to demonstrate that EEG effects associated with different aspects of performance can be examined in a single study – because the effects are dissociable in terms of their location on the scalp. For example, previous studies comparing experts and novices have examined theta in isolation (e.g., see Doppelmayr, Finkenzeller & Sauseng, 2008), whereas here it was identified alongside changes in alpha, beta and SMR. The present results highlight the need for future studies to broaden their analyses of the EEG spectrum, not only to identify different frequencies, but also as a first step towards understanding how the different effects interact to support successful shooting behaviour. In this regard it is notable that theories within the domain of motor control argue that a characteristic of expert performance is the meticulous planning and execution of the different elements of movements during the final stages of the preparation period (Keele,1986). The present findings highlight the possibility that EEG allows these different aspects of processing to be identified, each associated with distinct neural signals. As we discuss in more detail below, the present study provides support for the view that successful performance is associated with a number of distinct processes, each of which is reflected in specific changes in the EEG spectrum.

As we highlighted in the introduction, the dominant EEG effect examined to date is alpha power. In our study we identified that in the period just before shooters pulled the trigger (from -1000ms to 0ms) there was an increase for alpha power over parietal areas for unsuccessful performance compared to successful performance. In this respect our data is consistent with previous findings. For example, Salazar, Landers, Petruzezello, Han & Kubitz (1990) reported increased levels of alpha power during the pre-shot period associated with poorer performance in skilled archers. The authors suggested that the greater power exhibited for worst shots compared to best shots could indicate greater level of activation that is detrimental to performance. Similarly, Babiloni *et al*., (2008) reported changes in alpha power prior to successful versus unsuccessful golf putts. In this study a reduction in alpha power occurred prior to all putts, consistent with the idea that voluntary self-paced movements are characterized by a reduction within the alpha frequency range (8-12Hz). Importantly, however, in this case changes in alpha were reported over frontal midline electrodes, rather than the parietal effects reported here. Additionally, Babiloni *et al.,* (2008) had reported that compared to missed putts, successful putts were preceded by a larger reduction in alpha power (10-12 Hz) over Fz, Cz and C4 electrodes. Taken together, therefore, these findings suggest that changes in alpha may be associated with a number of different processes.

In the wider neuroscience domain, a large body of literature suggests that alpha increases occur in regions which are irrelevant to the task, whereas regions that are crucial to the task exhibit a reduction in power (Magosso *et al.,* 2019). Research has also suggested that when attention is externally driven alpha power decreases over parietal - occipital sites during visual stimulation (Mann, Sterman & Kaiser, 1996). This view of alpha is somewhat consistent with the effects reported here. As seen in Figure 3.6 and 3.12, as unsuccessful performance was associated with larger increases in alpha power compared to successful performance, over parietal electrodes immediately before the trigger pull (time window 3). More specifically, we observed lesser alpha power underlying successful compared to unsuccessful performance, a difference that was statistically reliable throughout the final time window. Given that greater external attention is associated with lower alpha power (Sauseng *et al.,* 2005), the changes in alpha power seen here might suggest that successful performance is achieved when shooters adopt a more visuo-spatial attentive state (i.e., spatial attention) towards the visual target. The lesser alpha power preceding successful performance compared to unsuccessful performance could reflect the notion that, athletes are mobilizing resources to support a spatially attentive state focusing on the visuo-spatial information available. From an applied perspective this raises the possibility that shooters might benefit from training that aims to enhance their ability to focus on the visuo-spatial information that is important for successfully hitting the target.

The present data also provided evidence that changes in alpha were temporally and topographically distinct from changes in theta. Whilst differences in alpha were present at parietal electrodes throughout the final second before the trigger was pulled, changes in theta were present at frontal electrodes, and only statistically reliable during the last 500ms. Whilst differences in frontal theta have been previously observed between experts and novices (e.g., see Doppelmayr, Finkenzeller & Sauseng, 2008), our examination of theta and performance suggests that more theta is present for unsuccessful compared to successful performance within experts. Kao, Huang and Hung (2013) used a within-subjects design to study skilled golfers' performance and reported lower theta at frontal electrodes during the pre-putt routine associated with superior putting performance. Cooke *et al.,* (2014) compared EEG neural activity between experts and novices during a golf putting task. The researchers found less theta was evident in the period preceding putts in experts compared to novices, consistent with prior evidence suggesting that lower theta power reflects processing associated with the top-down control of attention (Bakhshayesh *et al.,* 2011).

Chuang *et al.*, (2013) reported that during the preparatory period of unsuccessful basketball throws in elite basketball players, during the third (-1s to -0.5s) and fourth (-0.5s to throw) time windows an increase within theta power was observed. The researchers speculate that the players might have failed to maintain a stable arousal level with the increase of theta power resulting in higher mental effort and higher attentional resources which in turn were detrimental to performance. Frontal midline theta power is associated with information processing and ability to sustain attention; thus, the sudden increase within unsuccessful performance in the last 500ms prior to the trigger pull might reflect disturbances of the information processing flow resulting in an interruption and detriments to performance.

In addition to the neural patterns for alpha and theta, the present study also revealed a reduction in beta and SMR power between successful compared to unsuccessful performance. Both effects were associated with a greater activity for unsuccessful than successful performance during the last second before the trigger pull. Whilst beta was present bilaterally at electrodes over the central motor region, the SMR effect was left-lateralised (only significant over C3 electrode). Previous findings link changes in beta and SMR to motor processing. For example, Cooke *et al.,* (2014) suggested that a decrease of beta power, evident in their expert golfer population in comparison to novices, results in better programming of the movement during the preparatory period prior to athlete’s putting movement. Similarly, SMR in the hand area of the sensorimotor area decreases during movement planning or movement execution (Pfurtcheller *et al.,* 2006). In general, high SMR reflects cortical inhibition and low SMR reflects cortical activation (see Klimesch *et al.,* 2007). In line with our results, SMR seems to be lower in the successful compared to the unsuccessful performance, which might suggest a better movement plan underlying successful compared to unsuccessful performance.

Overall, therefore, an integrated view of the findings presented in this chapter points to the following suggestion: a similar pattern of changing neural activity is present across a range of frequency bands (parietal alpha, frontal theta and central beta and SMR), with each EEG effect exhibiting an increase in activity underlying unsuccessful performance during the last second prior to the trigger pull. The lower power of parietal alpha suggests that experts are processing visuo-spatial information obtained from the visual target within the second preceding the trigger pull, with lower power in frontal theta underlying successful performance suggesting an appropriate level of sustained focus and mental effort beneficial for the successful execution of the task, which will not interrupt the information flow processing during the final 500ms preceding the trigger pull.

At the same time, a decrease in central beta and lower SMR power during the last second prior to the trigger pull suggests that successful and unsuccessful shots differ in terms of the preparation and programming of the movement required (such as the force needed to pull the trigger and the stabilization of the pistol in the final second prior to taking the shot). The pattern of EEG effects suggests that the different elements of processing are engaged simultaneously to support performance, suggesting that future investigations may reveal further insight by examining the relationships between the processes (e.g., via connectivity analysis).

Whilst the present study demonstrates that mobile EEG can be used during the assessment of real sporting behaviour, the difficulty in establishing statistically reliable effects in the initial analysis highlights two key issues. First, unlike in the majority of sports related EEG research, here we employed a baseline correction procedure – comparing power measured during the pre-shot period relative to an earlier baseline period. To assess the suitability of the baseline we examined the stability of the EEG measure for successful and unsuccessful shots using a Root Mean Square measure, providing some confidence that the choice of baseline was not problematic (i.e., no differences were present in the baseline activity). Nonetheless, it remains unclear why baseline corrections are not typically employed in the sports literature, or what consequence this has when comparing findings – and this is an issue that we return to in later chapters. Second, consistent with the dominant approach in the literature we employed a 3 second epoch, analysed initially in 1 second time windows. Visual inspection of the time frequency plots shows, however, that many of the EEG effects were transient in nature. Moreover, in our targeted analysis we examined smaller 500ms time windows to better capture the effects. Whilst the approach employed here is relatively conservative (statistically), a more fine-grained data driven approach (tailoring time windows based on visual examination of the data) may be necessary to fully characterise the neural activity that is present – another issue that we return to in later chapters.

Finally, although the current experiment succeeded in revealing changes in neural activity associated with successful shooting, we highlight a key limitation of the findings from the perspective of the sports professionals. That is, whilst EEG methods have traditionally relied on the examination of group average data, sports professionals' primary goal is to gain insight into the processes supporting individual athletes' performance. In the present data there was some evidence of variability across the athletes. When examining the behavioural performance of our participants on an individual level it was clear that there was considerable variability in the mean and range of scores. In this respect the use of kinematic data (measurement of movements of the gun during firing) might provide a more comprehensive view of the individual differences in sporting behaviour across athletes. Equally, it is also clear within the wider EEG literature that some of the neural signals measured in the current study are subject to individual variability. For example, previous research suggests that the frequency band associated with changes in alpha can vary across individuals – such that an individually tailored “peak” alpha frequency can be identified for each individual (Angelakis *et al.,* 2004). As a result, the use of a pre-screening procedure that allows alpha to be defined individually in each athlete could significantly influence the outcome of the EEG analyses, making this an important issue for future research to address. In short, therefore, whilst the present focus on characterising successful performance in experts is a significant advance (over comparisons between experts and novices), it remains one step removed from an individual approach. Ultimately, sport practitioners are interested in understanding the specific patterns of neural activity associated with different levels of performance at an individual level. Do all expert athletes exhibit the same EEG profile characterizing successful performance? Or does each individual athlete acquire different processes to perform at the highest level? To begin to address these questions the next chapter presents a study using an air rifle shooting task, focusing on two elite athletes, and examining the individual EEG profiles characterizing successful versus unsuccessful performance within each athlete.

Chapter 4: Identification of Individual Alpha Peak Frequency and the exploration of the neural dynamics characterizing successful and unsuccessful performance between two elite athletes.

4.1 Introduction

According to Park, Fairweather & Donaldson (2015) the findings from cognitive neuroscience research undertaken in the sporting domain has not had a major impact on sporting practice mostly because of the low ecological validity of the tasks used. Although this is true, the lack of research focusing on understanding individual athletes and the failure to take into account individual differences (either at a behavioural level or a neuronal level) are additional reasons why research in the sporting domain has not had an impact on professionals and athletes.

The importance of individual variability is easily illustrated in relation to alpha power. As outlined in Chapters 1 and 3, research has investigated the alpha frequency band (8-12Hz) by comparing expert and novice athletes, or by examining the relationship between alpha frequency power (8-12Hz) and performance at specific pre-chosen electrode sites. However, research in the wider neuroscience literature has provided evidence of inter-subject differences in the alpha frequency range, in relation to an individually identified “peak” in the spectral analysis within the alpha frequency range. The identification of such individual differences between athletes will be an important step towards the understanding of the functional role of alpha oscillations in sports and its potential causal association with successful or unsuccessful individual performance.

In order to examine individual variability at a behavioural and neuronal level, the current chapter focuses once again on examining EEG and kinematic data in air rifle shooting. More specifically, we examine two expert athletes over a series of shooting sessions, exploring whether there are specific patterns of neural power associated with different levels of performance within each individual athlete and whether these patterns are similar or different between individuals. The suitability of shooting for EEG research was previously discussed in Chapter 3 (see section 3.1 Introduction). More importantly for present purposes, shooting is also suitable from an applied practice perspective, because it does not involve direct interaction between athletes; each individual's training and development routine is unique, thus the kinematic data provide additional information concerning the training routine of individual athletes. As a result, athletes and coaches are particularly interested in understanding any differences in cognitive and neural processing that might distinguish successful performances at an individual level.

Before outlining the current study in more detail, the following sections first introduce the literature on individual alpha peak frequency, providing a rationale for the examination of individual alpha peak frequency in a shooting task. Additionally, as this study recruited only two elite athletes, information will be provided about previous research that has used small samples, including the implications for statistical analysis.

4.2 Individual Alpha Peak Frequency

In 1929, Hans Berger discovered the first EEG wave that he named “alpha” rhythm. Alpha band oscillations are the most dominant frequency in the human brain and usually range from 8-12Hz. Importantly, early findings demonstrated that the amplitude of alpha power reaches its peak when participants are in an eyes-closed state and that the sensory input that occurs in an eyes-open state leads to a reduction in alpha amplitude (Berger, 1929). Almost a century later Cheron *et al. (2016)* suggested that alpha oscillations can be regarded as an electroencephalographic biomarker, useful for exploring neural power in a sporting context. Alpha power has, however, been widely studied from a neurocognitive perspective, and is thought to be involved in a number of different stages of processing, influencing both sensorimotor processes (Bernstein, 1966) and cognitive performance (Klimesch *et al.* 1993). Whilst a detailed review of the wider literature is beyond the scope of the current Chapter, it is important to acknowledge that there is considerable evidence (e.g., see Klimesch, Sauseng & Hanslmayr, 2007 on the inhibition hypothesis) characterising alpha as a marker of inhibition.

According to research investigating individual variability in brain power (e.g., see Doppelmayr et al., 1998; Klimesch, 1999), a ‘’peak’’ can be identified within the alpha frequency spectrum (7.5-12.5Hz), which can be used as a marker to distinguish between upper and lower alpha bands. Formally, the Individual Alpha Peak Frequency (IAPF) has been defined as the maximum peak in the EEG alpha frequency spectrum between 7.5 and 12.5Hz (Klimesch, 1999). Although previous research has shown inter-individual IAPF differences, the majority of studies tend to define the alpha rhythm with the most common band range of (8-12Hz) and use this predefined band to average EEG power across all subjects, without accounting for individual differences (Haegens *et al.,* 2014).

Research within the alpha frequency domain has suggested various differences across individuals within the alpha frequency, linked with differences in cognitive performance (Klimesch *et al.,* 1999). Recently research has shown that individual alpha peak frequency can predict performance during perceptual (Samaha & Postle, 2015) and cognitive (Klimesch, Doppelmayr & Hanslmayr, 2006) tasks. More broadly, research in the domain of the individual alpha frequency has established inter- and intra-individual differences (Angelakis *et al.,* 2004). The variability differences between individuals, within the alpha peak frequency is mostly explained by genetic factors (Malone *et al.,* 2014). Quantification of the individual differences within the alpha frequency domain can be used to extract individual values for subjects within the alpha frequency (Klimesch, 2012). Additionally, individual alpha peak frequency differences within individuals have been linked to differences in the engagement of attentional processes during performance of a task and to variability in the arousal states of the participant performing the task (Klimesch *et al.* 1990).

Taken together, the existing research suggests that estimating individual alpha frequency bands will provide a more precise frequency domain analysis (Klimesch, 2012). According to Haegens *et al.,* (2014) knowing the range in which the alpha frequency operates for an individual, should provide a basis for a better interpretation of the pattern of results compared to examining differences in performance in terms of the standard alpha power definition. Moreover, when analyses do not account for individual differences within the alpha frequency range, evidence suggests that power from neighbouring frequencies (e.g. theta), might be included in the pre-defined (8-12Hz) alpha windows - which would clearly lead to erroneous interpretations (Klimesch, 1997). Thus, Klimesch (1999), argues that the use of IAFP calculations for each individual provides a more accurate estimation of the effects present and therefore improves the interpretation of results. Previous literature has also used individual alpha peak frequency estimations to define the neighbouring theta and beta frequency bands to eliminate any overlap between the frequencies (Babiloni et al., 2012).

Additionally, it has been suggested that when the IAFP is calculated for each individual, further subdivisions within the alpha peak frequency of high- and low-alpha ranges should be defined, as high- and low-alpha ranges might operate differently under specific tasks (Klimesch *et al.,* 1996,1998). For example, it has been suggested that decreases in the lower alpha power band varies as a function of attentional demands whereas higher alpha power decreases are associated with semantic memory demands (Klimesch et al., 1996).

Some studies have extended the investigations of the alpha peak frequency during actual performance in the sensorimotor domain. Huldunsker, Mierau and Struder (2016) reported that during balance tasks which varied in surface stability and base of support, increase in upper alpha frequency was associated with balance controls which required higher demands of stabilization and with decreases in lower alpha power. The increase of high alpha power was observed in the frontal-central region and the decrease of low alpha power was observed globally. However, most studies in the sporting literature define alpha rhythm as a fixed narrow band (8-12Hz) and average the spectral power within the 8-12Hz fixed band across all participants. Some researchers within the sporting literature have used individual alpha peak frequency to define individual alpha bandwidths (Del Percio *et al.,* 2009; Babiloni *et al.,* 2010), but the previous research did not investigate any possible connection between the individual alpha peak frequency of athletes and successful/unsuccessful performance.

For example, in the case of Del Percio *et al.,* (2009) the researchers were investigating the underlying mechanisms (using EEG data) during two different standing positions in elite karate and fencing athletes and non-athletes. The researchers determined individual alpha sub-bands, using the peak frequency approach, allowing them to identify a mean peak for each group (fencing, karate, non-athletes) within the alpha frequency. The results suggested that low (about 8-10Hz) and high- (about 10-12Hz) alpha frequencies reflected different mechanisms underlying neural efficiency within the elite groups of athletes.

The most common approach used within the wider literature for alpha peak frequency calculations is the peak frequency method (Goljahani *et al.* 2012). Peak alpha frequency defines individual alpha frequency based on the highest peak identified within the alpha bandwidth, usually defined as 8-13Hz (Corcoran, Alday & Schlesewsky, 2017). Thus, the peak alpha frequency identification is based upon identifying the highest peak within a predefined range of frequency. Thus, for the purposes of this PhD, the peak frequency method has been chosen for defining individual alpha frequency bands, on the basis of its simplicity and to follow previous research within the literature (Goljahani *et al.* 2012). It is important to acknowledge, however, that the peak frequency method has been criticized on the basis that it cannot be applied when multiple peaks are present within the EEG data or when the EEG spectra power is flat, and no visible peak is existent. The alternative approach used within the IAFP literature is the centre of gravity frequency.

In theory, the use of individual alpha peak frequency analysis will provide a more accurate estimate of the alpha power for each individual (Doppelmayr et al., 1998) and more accurate estimations of neighbouring frequencies such as theta, thereby providing a basis for a more accurate interpretation of the pattern of results. Moreover, it has been suggested that the individual alpha frequency should be divided into low- and high- subranges of alpha, as evidence has shown that they may behave differently under different task conditions (Klimesch et al., 1998). Thus, in line with previous suggestions, in the present study the individual alpha peak frequency will be divided into high- and low- range frequencies. The move towards a tailored approach is supported within the sports literature. For example, Hammond (2007) mentioned that each individual requires a different approach. The simplistic one-size-fits-all approach in sports is likely to be ineffective across sports and individuals. As Arns *et al.,* (1991) have argued the training for performance enhancement can be highly variable across individuals. Therefore, investigating IAFP and performance is a crucial step required in the sporting literature to identify any individual differences within the frequency bands differentiating successful and unsuccessful performance within each individual.

4.3 Small number studies

A key struggle in studying elite athletes is the reliance on small sample sizes. The statistical power of a study (i.e., the probability that a significant effect will be detected, if it exists) is directly linked to the sample size. In traditional analysis, statistical methods rely on large sample sizes, and as a result the collection of large samples is widely encouraged. Decreasing the sample size reduces the ability to detect any differences, thus it is likely that in small sample studies only very large effects will be able to be detected (Morgan, 2017). It is also acknowledged, however, that in specific areas of research (including elite sports) it is only possible to work with small sample studies (Ioannidis, 2013). For example, small sample studies are commonplace in preclinical research in studies involving animals and clinical populations (Morgan, 2017). These kinds of situations raise the question of whether single case study data can be subjected to formal statistical testing.

Single case design studies are also used within a number of psychology fields, including autism research, developmental disorders, language disorders, neuropsychology, sport and exercise psychology (Shadish & Sullivan, 2011). For example, one domain in which single case studies are unavoidable is within the domain of cognitive neuropsychology (Medina & Fischer-Baum, 2018). Researchers in cognitive neuropsychology use data from individuals with brain damage to further understand the organization of the ‘’typical’’ cognitive system (Medina & Fischer-Baum, 2018). Assessing neuropsychological deficits in an individual case usually involves the comparison of that individual score on a neuropsychological test with the scores obtained from a neurotypical sample of individuals (Crawford & Garthwaite, 2004). In such cases, the patient’s performance is quantified by using the slope of a regressions line and comparing that slope with the scores from a control sample (Crawford & Garthwaite, 2004). For example, within the motor control area, researchers compare the slopes of the regression lines relating to object size and grip between healthy participants and the patient of interest (Crawford & Garthwaite, 2004).

The approach used within the neuropsychology literature does not, of course, provide a solution here because we are not comparing our elite athletes to a sample of the general population. Instead, we are specifically interested in investigating the neural power in successful/unsuccessful shooting performance within each individual. Researchers adopting this approach are, therefore, forced to analyse data in alternative ways (Trafimow & Marks, 2015). One example of an analytic approach that has become increasingly common in Psychology is the use of Bayesian statistics, which can in principle be applied to both groups and individuals. Unfortunately, however, one of the requirements for the Bayesian approach is good (i.e., reasonable, reliable) ‘priors’ - that is information from previous studies that provides a basis for the statistical analysis (Gupta, 2012). Whilst Bayesian analysis is powerful where reliable ‘priors’ are available, this is not possible in relation to individual differences in EEG during sports because no data exists to inform reasonable priors.

Another alternative approach is to simply abandon formal testing when examining individual cases. For example, previous literature in the sporting domain has used visual inspection of frequency scalp maps to characterise differences across levels of performance (Di Fronso *et al.,* 2016). Di Fronso *et al.,* (2016) were interested in identifying neural markers associated with shooting performance using the Multi-Action Plan (MAP) model to categorize performance in one elite air-pistol shooter. The MAP model is used to capture performance experiences of athletes in which they are able to perform successfully under either automatic or controlled states (Di Fronso *et al.,* 2016). Type 1 performance state is characterized as optimal performance that is automatic (minimal conscious control leads to successful performance). Type 2 reflects optimal performance that is controlled (more focused control and successful performance). Type 3 reflects suboptimal performance that is controlled (high level of conscious control leading to unsuccessful performance) and Type 4 is suboptimal performance that is automatic (ineffective minimal control leads to unsuccessful performance). The researchers used this descriptive approach to characterise neural differences associated with variability in shooting accuracy. Additionally, the researchers used visual inspection to assess the scalp maps across three one second time windows.

Based on visual inspection alone, the researchers reported that the four different types of the MAP model were characterized by different neural power patterns. Furthermore, they suggest that successful performance does not always occur in automatic states, but also in controlled states where the athlete consciously concentrates on the sporting task (Type 2 performance). Type 1 (optimal-automatic) and Type 4 (suboptimal-automatic) performance states were characterized as automatic, reflected in the decrease of low alpha frequency (8-10Hz) which was suggested to reflect relaxation states (di Fronso *et al.,* 2016). By contrast, Type 3 (suboptimally controlled) performance state was characterized by an increase within the alpha frequency, suggesting an increase in attentional focus leading to unsuccessful performance. Importantly, however, Type 2 performance (optimally controlled) was also characterized by a slight decrease of alpha and beta power, leading the researchers to suggest that expert athletes can achieve successful performance when they are consciously focusing their attention on a critical component of the task.

Whilst the visual inspection approach adopted by Di Fronso and colleagues clearly has some merit, the outcomes are also open to a greater degree of interpretation than traditional statistical results. Not surprisingly, therefore, Shadish (2014) argues that single case study designs are not fully accepted by the scientific community due to the failure to use traditional statistics to analyse single case studies. Equally, however, the traditional statistical approaches employed within psychology are considered problematic in some respects. Notably, Cumming (2014) suggests that changes are needed to the way that researchers perform and carry out research, particularly the use of traditional Null Hypothesis Significance Testing (NHST).

The NHST approach compares two statistical hypotheses. The alternative hypothesis, which are the researcher's predictions (i.e., that the different conditions should differ), and the null hypothesis which suggests that no difference exists between conditions (Levine *et al.,* 2008). In a standard NHST, researchers have an *a-priori* alpha level of significance, which is usually set at 0.05. If the *p* value of a statistical test is less than or equal to the chosen alpha level, then the null hypothesis is rejected, leading to the claim of statistically significant differences across the observations the researcher is interested in. In practice, however, the NHST approach can be problematic, leading Ioannidis (2005) to refer to the NHST approach as 'flawed'. As noted above, the NHST approach is sensitive to the sample size (Boster, 2002). Strong and important effects can be regarded as non-significant if the sample size is small, however, if the sample size is large, even very small effects can be regarded as significant. In addition, however, Ioannidis (2005) argues that most researchers focus on achieving statistical significance within their results, as it is the main criterion for accepted publications (and to gain research funding). Similarly, Simmons, Nelson and Simonsohn (2011) argue that restricting information about the data collection and analysis can allow the presentation of almost any data as significant. The authors argue that researchers can easily manipulate test results by adding participants, removing, or adding dependent variables, selecting which components to analyse, or trying different analysis strategies to finally select what is the best information to report.

Given the growing concerns about the NHST approach Cumming (2014), suggests an approach to overcome the flaws of NHST. According to this view descriptive statistics can be used in research to calculate, describe, and summarize research data in a logical and efficient way (Vetter, 2017). Critically, descriptive statistics can sit alongside visual inspection to provide a formal (quantifiable) assessment of the data. Descriptive statistics provide information on important characteristics of the data by examining the central tendency of the data, like the mean, and measures of dispersion, like the standard deviation or confidence intervals. According to Cumming & Calin-Jageman (2017) in their book ‘’Introduction to the new Statistics; Estimation, Open Science, & Beyond’’, using estimation statistics such as Confidence Intervals (CI) is a particularly informative way to analyse data because they quantify uncertainty (i.e., the length of a Confidence Interval (CI) is a measure of the extent of uncertainty in our point of estimate of the mean).

Overall, in principle, the new statistics approach suggested by Cumming & Calin-Jageman (2017) is descriptive, whereas the NHST is an inferential statistic. If researchers just wish to describe their data, then reporting the mean and variance is appropriate; however, if researchers wish to draw conclusions from the data to support empirical claims, then there is a necessity to specify what information constitutes sufficient empirical evidence. In practice, however, the new statistics approach is mathematically equivalent to NHST when 95% confidence intervals are examined: If the 95% Confidence Interval’s for two means do not overlap (or the 95% CIs of a single condition does not include 0) this is formally equivalent to establishing that the two means are different with a *p* value of less than 0.05 (or that a single condition is reliable different from 0 with a p value of less than 0.05). From this perspective, therefore, the use of 95% CIs allows inferential conclusions to be drawn from descriptive statistics, even if formal statistical analyses have not been carried out.

Taking into consideration the small sample size (N=2) in the current study, the difficulties associated with NHST and issues arising with the Bayesian approach due to unavailable prior information, here we employ a ‘new statistics’ approach. Descriptive statistics will be used to characterise the pattern of results, based on the means and 95% confidence intervals associated with the data. Whilst this approach is novel in the context of sports EEG, the new statistics literature suggests that it should provide a robust basis for interpreting the pattern of results, allowing inferences to be drawn from the data.

4.4 Rationale for exploring neural power in two elite athletes.

As highlighted above (and see Chapter 1), to date the sports literature has largely focused on the identification of brain-behaviour links comparing experts to novices or has examined neural power using abstract non-sporting tasks. By contrast, the key focus here is to examine the neural differences between successful versus unsuccessful performance in individual expert elite-level athletes. Although previous research provides a valuable first step, from an applied sports practitioner perspective the overriding goal is to understand brain-behaviour links within an ecological valid setting, with value placed on understanding the differences in neural power that underlie the highest levels of behavioural performance within each individual. Whilst the rationale for sports professionals is to gain information that could help improve performance, the same logic applies from a cognitive neuroscience perspective. Put simply, studies comparing expert and novice athletes are unable to fully address the question of how experts achieve consistently high levels of performance; this can be addressed by examining experts, using a representative task to assess real sporting behaviour.

At this point it should be clear that the current study does not aspire to resolve all the issues regarding the variable approaches and inconsistencies that exist within the literature. Instead, the aim is to understand and investigate individual skilled performance during real world sporting performance, using a genuinely representative task. Critically, the data collection procedures employed in the current study have been developed in association with the athletes and coaches, to ensure that they do not disrupt normal practice routines. As was highlighted in Chapters 1 and 3, a major limitation of most EEG studies of sporting behaviour is that they were undertaken in laboratory settings, raising obvious concerns about ecological validity. Additionally, the sporting literature does not account for individual differences in athletes. In particular, sports EEG studies have not accounted for variability in the individual alpha peak frequency - as Haegens et al., (2014) note, most EEG studies define alpha rhythms in a fixed narrow band of (8-12Hz), which is the case in the sporting literature. Given the focus on individual athletes, here we employ a more precise estimation of modulations in alpha power by determining the IAFP of each individual (Klimesch, 1999; Haagens et al., 2014).

The study will employ two elite Air-Rifle shooters. The data collection process in the current study was developed in collaboration with the athletes and their coach to reflect realistic normal practice routines. Thus, in order to collect as many trials as possible (for EEG processing and analysis), EEG data acquisition had to be conducted over a number of sessions. Because of differences in the training and competition commitments of the two athletes we were able to collect EEG and behavioural data from Participant 1 over six sessions, but only four sessions for Participant 2. The following sections will outline the methods, procedure, and processing analysis for this chapter, followed by the results section which will examine the neural power within each athlete - characterizing successful and unsuccessful performance by identifying the Individual Alpha Peak Frequency, and extending the examination to the theta, sensori-motor rhythm and beta frequency ranges.

4.5 Methods

4.5.1 Participants

The study employed two female participants (N=2), experts in target air rifle shooting. Participants were recruited through Sport Scotland and both shooters were elite athletes engaged in International-level competition at the time of recording. Both participants were right-handed, right eye dominant and had normal or corrected eye vision. The participants were 21 and 26 years old. The experiment was reviewed by the General University Ethics Panel (GUEP) of the University of Stirling. The athletes took part in the research voluntarily, understood the experimental process and purpose, and provided written informed consent to participate. For ethical reasons participants cannot be named, thus we will refer to them as Participant 1 and Participant 2.

4.5.2 Experimental design

The shooting range was located in Edinburgh and all procedures followed the International Guidelines (ISSF General Regulations, 2020, p.6) of the shooting association. The 10-metre air rifle shooting task consisted of 40-60 shots, shot towards an electronic target. EEG data was collected using a representative task design, based on the athletes standard training between competitions. The participants were asked to follow their normal training routine whilst performing the task, to keep the experimental sessions as close to the naturalistic setting of the sport as possible.

EEG was recorded continuously throughout practice, with time locking triggers generated by a custom-built acoustic box and through a manual button press trigger when each shot was fired. The custom-built acoustic box could not dissociate the sound from the Air-Rifle and other surrounding noises; thus, a manual button press was made by the researcher each time a shot was fired to confirm which acoustic triggers were of interest and associated with the shot. The triggers used to mark the EEG events were the triggers sent by the acoustic box. EEG was recorded over a series of sessions; a repeated session design was adopted to provide as many trials as possible, without disturbing the shooters' typical practice routines. The participants were asked to wear their standard shooting gear whilst performing the task, to keep the experimental session as close to the naturalistic setting of the sport as possible, as illustrated in Figure 4.1.

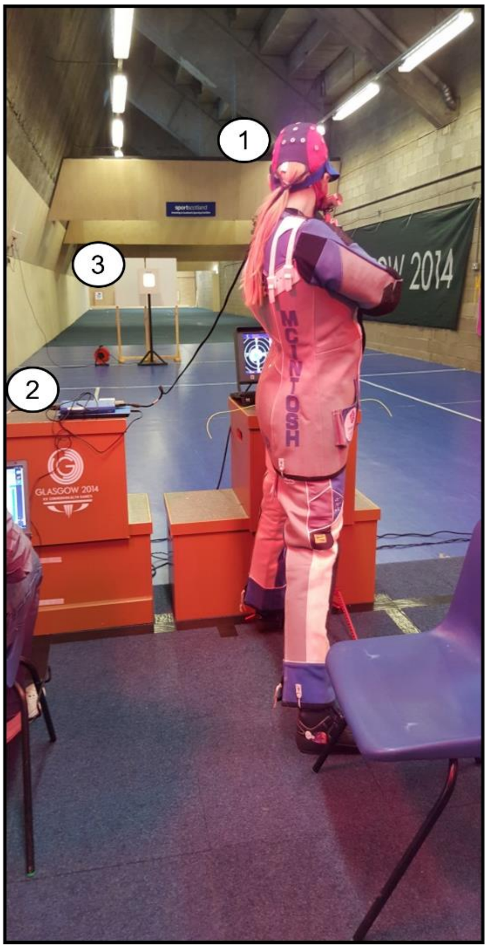


Figure 4.1. An example of the mobile real-world shooting experimental setup. [1] EEG sensors, [2] Amplifier, data storage unit and acoustic trigger box, [3] 10m Air-Rifle shooting target. Note that event triggers are implemented through an acoustic trigger box and through a manual button press from the experimenter.

The score associated with each shot was recorded, allowing EEG data to be examined as a function of performance. The highest score achieved in air rifle shooting is 10.9, and for the purpose of this research performance was individually categorised into two levels. The choice of classification for successful and unsuccessful performance was calculated on an individual basis for each athlete (outlined in further detail in the results section 4.6).

4.5.3 Material

EEG data was recorded via 32 Ag/AgCl electrodes located in an elasticated headcap and connected to a battery powered portable amplifier (ANT-NEURO, Enschede, The Netherlands). The digitization rate of the system was set at a sampling rate of 500 Hz, and data were prefiltered with a high pass filter of 0.0016 Hz and low pass filter of 250Hz. The electrodes were positioned according to the International 10-20 system (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2). Electrode AFz served as the ground electrode and CPz as a common reference. Electrode impedance was measured prior to each recording session and each channel was maintained below 10 kΩ. The timestamping of the events was achieved through an acoustic box, which marked the shot, and a manual button press to verify the shot.

Shooting performance was studied based on six kinematic indicators via an electronic device called ‘’SCATT’’. The SCATT system is a computer training accessory that provides the opportunity for shooters and coaches to explore what is happening while the shooters are aiming towards the target. SCATT provides information on 6 different indicators, which will be described below in detail based on the descriptive information provided by the coach: a)Time: Provides information on the time taken to fire each shot [from lifting the Air-Rifle and aiming towards the target (engagement with shot) to pulling the trigger], measured in seconds. b) 10a0 and 10a5:

Defines the percentage of the last three seconds of aiming time where the point of aim is within the 10.0 and 10.5 scoring zone compared to the centre of the aim in the same period. c) mm/s and mm/s/250: The speed of the point of aim across the target in the last three seconds before the shot, and also in the last 250ms before the shot. d) Breach: A measure of the distance between the centre of the aim (in the last three seconds) and where the shot lands on the target.

4.5.4 Procedure

Prior to the experiment, the participants were given general information regarding the functional and practical aspects of the EEG technique recording in both verbal and written formats. Participants were informed that the experiment was conducted in accordance with the guidelines of the University of Stirling Research Ethics Committee (GUEP), that their data would be stored and treated anonymously, and that they had the right to end their participation in the study at any time without any consequences. Participants were then invited to provide their written consent to confirm their voluntary intention of taking part in the study.

During the capping procedure, which took approximately 45 mins, participants were seated on a chair in the shooting range. Measurements of each participant's head were used to set up the scalp location sensors based on the International 10-20 system (Jasper, 1958) – note that care was taken to ensure consistent placing of the cap across sessions, to facilitate the averaging of data. The gap between each electrode and the scalp was filled with conductive gel, and the experimenter used a disposable blunt needle to increase the sensor conductivity. The electrode impedance was kept below 10 kΩ for each channel.

Following capping, participants were asked to remain seated and chose a point in the environment to focus on. A total of two minutes of eyes open and eyes closed EEG resting conditions were recorded starting with eyes closed and then alternating between conditions every 10 seconds which was used for the Individual Alpha Peak calculation. At the end of the recording, participants were asked to undertake a short training session to warm up, which consisted of 10-20 shots towards an electronic target. The participants let the experimenter know when they felt ready to start the experiment. Participants were instructed to follow their normal training routine and, if required, to take breaks between every 10 shots. Once data collection was completed, the electrode cap was removed, and participants were debriefed. The EEG data was then exported using the built-in data acquisition software (ASA, ANT-neuro). Continuous data was then stored on an encrypted hard drive, before proceeding with further processing.

4.5.5 Data Processing

EEG data were analysed using the EEGLAB open-source toolbox (Delorme & Makeig, 2004) and custom MATLAB scripts (version 2014, The Mathworks Inc.). At the preprocessing stages the continuous data were visually examined and segments that displayed high levels of noise (e.g., channel disconnections) were manually rejected. Following the removal of noisy data, each dataset was then filtered with a low pass filter of 40 Hz and a high pass filter of 1 Hz. Next, Independent Component Analysis (ICA, Bell & Sejnowski, 1995) was performed on each dataset, identifying a set of Independent Components (ICs) (e.g., a total of 30 components for each dataset) for consideration as artifacts. The ICs were assessed using SASICA (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact Correction, Chaumon, Bishop & Busch, 2014) to identify artifactual ICs for rejection. Although SASICA allows manual rejection of components (e.g., based on visual inspection) to ensure consistent application of the algorithm any ICs identified as artifacts were removed from the data. Table 4.1 below exhibits the number of ICs removed for each session.

	Participant 1	Participant 2
Session 1	22	17
Session 2	20	20
Session 3	16	17
Session 4	17	22
Session 5	17	-
Session 6	16	-

Table 4.1. Exhibits the ICs removed for each session and each participant based on SASICA identification of ICs as artifacts.

Following the ICs rejection, the data were epoched using a time-window leading up to the air-rifle shot (from -15000 ms to 0 ms, where 0 indicates the trigger pull). Epochs were visually inspected and epochs presenting obvious artifacts were discarded from further analysis. Baseline correction was carried out by dividing the EEG data of interest by the equivalent power during the baseline period, scaled as a percentage change (%). The SCATT device, (used for capturing kinematic data) provided additional information about when each shooter had engaged with the shot, by investigating the variable time (see section 4.6.3 for additional information). The timing information provided from the SCATT device could be used as an indicator of when each shooter picked up the Air-Rifle and started engaging with the shot (a laser beam is attached to the end of the Air-Rifle and once the laser has been pointed to towards the target the SCAAT starts timing the shot). Thus, by using the additional information provided by SCATT it was possible to calculate the time each shooter was engaged with the shot, providing an empirical basis for defining an appropriate baseline period. Figure 4.2 provides a histogram for Participant 1 representing the timing information provided by the SCATT device and the number of trials within successive time frequency ranges (i.e. bins). For Participant 1 we identified that an appropriate baseline period would be -15000ms to -14000ms prior to the trigger pull.

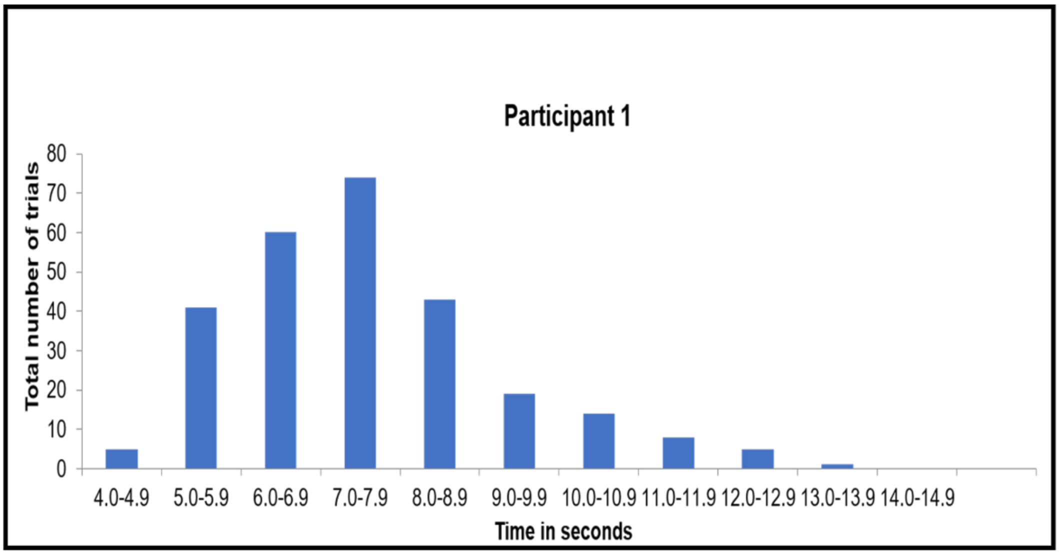


Figure 4.2. The histogram represents the frequency distribution of the number of trials (for participant 1) within each time range bin. The x-axis represents the time in seconds and the y-axis represents the total number of trials.

Figure 4.3 illustrates the equivalent data for Participant 2, indicating a shorter preparation period for this athlete. On the basis of these data, we identified that an appropriate baseline period would be -12000ms to -11000ms prior to the trigger pull. Due to technical issues with the SCATT device, the first 30 trials (included in the EEG analysis) are not included in the analysis for the SCATT variables for Session 1 for Participant 2.

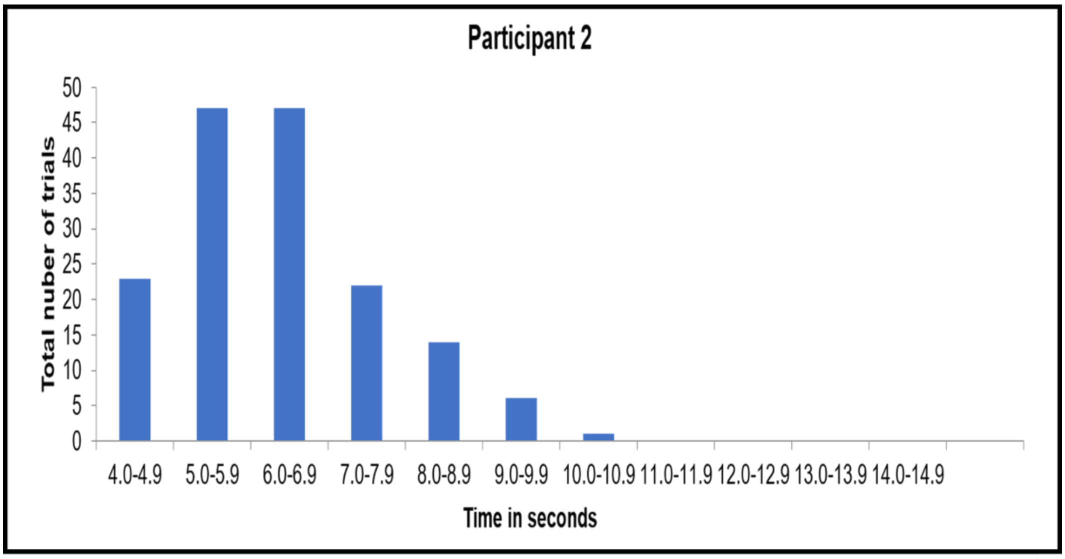


Figure 4.3. The histogram represents the frequency distribution of the number of trials (for participant 2) within each time range bin. The x-axis represents the time in seconds and the y-axis represents the total number of trials.

Additionally, and in line with the literature, the timing information provided by the SCATT device suggests that examination of a relatively brief -3000ms to 0 recording epoch is an appropriate period of interest to investigate. As it is clear from Figures 4.2 and 4.3 the use of a longer epoch of interest (up to 5- or 8-seconds pre-shot) would mean that most shots would fall in the category where the shooters are picking up the Air-Rifle and starting the process of engagement with the shot.

To explore the spectral dynamics of the data over time, a time-frequency analysis was conducted through the convolution of Morlet wavelets (9 cycles at the lowest frequency and a maximum of 32 cycles at 40Hz for the highest frequency) across the epoch. Event-Related Spectral Perturbations (ERSP) were computed by normalizing Event-Related Spectra, dividing the period of interest by the baseline period on a single trial basis (the choice of baseline is discussed in detail below). Event-Related Spectral Perturbations can be regarded as a generalization of the ERD/ERS analysis. The ERSP measures average dynamic changes in the amplitude of any given on-going EEG frequency as a function of time (relative to the experimental event of interest – in this case, the trigger pull). Overall, therefore, the ERSP measure reveals the average time course of relative changes in the EEG frequency spectrum (Makeig, 1993). To investigate neural power prior to the initiation of the trigger pull, EEG data were examined starting at 3 seconds prior to the shot, based on the triggering markers acquired from the acoustic box (time-locked to the trigger pull). This 3 second epoch window was selected to match the most commonly used epoch in previous studies examining shooting performance (see Del Percio *et al.,* 2009; Doppelmayr, Finkenzeller & Sauseng, 2008; Loze *et al.,* 2001), allowing comparison between the current findings and those reported in the existing literature

To identify the individual sub-bands for each participant, the individual alpha peak frequency was calculated according to guidelines within the literature (Doppelmayr *et al.,*1998). A wider alpha band (7-14 Hz) was chosen to explore the individual peak alpha, as it has been shown in previous literature that alpha rhythms operate across a wider frequency range (Haegens *et al.,* 2014). The average peak frequency was calculated from parietal (P3/Pz/P4) and occipital (O1/Oz/O2) electrode sites (Haegens et al., 2014). According to previous literature the ‘eyes closed’ condition is an optimal experimental condition for determining individual alpha peak frequency (Klimesch *et al.,* 1993), thus the 'eyes closed’ condition was chosen for the calculation of the individual peak frequency.

Participant 1 individual alpha peak frequency with eyes closed was 11Hz. Thus, for Participant 1 the frequency sub-bands were defined with respect to the individual alpha peak frequency as follows: a) alpha (9-13Hz), alpha 1 (9-11Hz), alpha 2 (11-13Hz), theta (5-8Hz), SMR (13-15Hz), beta (15-30Hz). Participant 2’s individual alpha peak frequency with eyes closed and eyes open was 10Hz. Thus, for Participant 2 the frequency sub-bands were defined with respect to the individual alpha peak frequency as follows: alpha (8-12 Hz), alpha 1 (8-10Hz), alpha 2 (10-12Hz), theta (4-7 Hz), SMR (13-

15Hz), beta (15-30 Hz). In short, the IAFP approach results in adjusted frequency ranges for just one of the athletes.

Power relative to baseline values (in %) were compared over time, between conditions, across frequency bands as described above. Data from each frequency were subjected to statistical analyses (descriptive statistics including 95% Confidence Intervals) which examined alpha and beta frequencies within the one second time windows in line with previous literature. Data from each frequency band was analysed independently, as a function of performance level (successful/unsuccessful), across three-time windows of interest and within each region (Frontal/Central/Parietal/Occipital), including a set of electrodes for each region (F3/Fz/F4; C3/Cz/C4; P3/Pz/P4; O1/Oz/O2) in line with Del Percio *et al.,* (2009). For the theta frequency (5-8Hz, for Participant 1)/(4-7Hz, for Participant 2) descriptive statistics and confidence intervals (95%) will focus only at the frontal location, in line with previous literature (e.g., Doppelmayr, Finkenzeller & Sauseng, 2008) and for the SMR frequency (13-15Hz) analysis was focused on the central region (Cheng et al., 2014).

Finally, to assess data quality and the choice of baseline period we examined variability in the baseline via the Root Mean Square (RMS, i.e., the arithmetic mean of the squares of a set of values). RMS was calculated independently for successful versus unsuccessful shots, across the entire baseline period, to determine any deviation in signal quality across conditions that might affect the interpretation of the results in the specific frequency bands. RMS was applied to all electrodes chosen to be analysed in this study, and examined for each participant individually, to provide insight into the overall quality of the EEG recording.

4.6 Results

Shooting Behavioural performance

	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6
Mean	10.2	10.2	10.1	10.3	10.1	10.1
Maximum	10.8	10.8	10.8	10.9	9	8.8
Minimum	9.5	9.1	9	9.5	10.8	10.9
N (total shots)	40	40	40	30	60	60

Table 4.2. The table illustrates the mean, maximum minimum shooting scores and total shots acquired in each session for Participant 1.

	Session 1	Session 2	Session 3	Session 4
Mean	10.4	10.3	10.3	10.4
Maximum	10.9	10.9	10.9	10.8
Minimum	9.7	9.5	9.7	9.6
N (Total Shots)	55	60	40	40

Table 4.3. The table illustrates the mean, maximum minimum shooting scores and total shots acquired in each session for Participant 2.

Table 4.2 and 4.3 exhibit the mean, maximum, minimum and N of the behavioural scores provided in each session, for each participant, respectively. Participant 1 provided 270 trials in total, and Participant 2 provided 195 trials in total. Behavioural performance in successful and unsuccessful categories were assessed on an individual basis. The categorization scores for each athlete were performed using an average split for each participant throughout all sessions provided. Table 4.4 below outlines the categorization scores of each participant in successful and unsuccessful performance. Participant 1 successful performance was considered with scores above 10.2 and unsuccessful performance with scores 10.1 and below. Participant 2 successful performance was considered with scores above 10.4 and unsuccessful performance scores 10.3 and below.

	Participant 1	Participant 2
Sessions	6	4
Successful	10.2-10.9 (159 trials)	10.4-10.9 (112 trials)
Unsuccessful	8.8-10.1 (111 trials)	9.5-10.3 (83 trials)

Table 4.4. Behavioural performance and shooting categorization scores for each athlete.

Having established individually tailored definitions of the boundary between success and unsuccessful shots, we examined the relationship between performance and the SCATT indicators in more detail. For each athlete, a series of Pearson (two-tailed) correlations were used to compare the score on each shot with the corresponding SCATT variables. Bonferroni correction for multiple comparisons was performed and statistical significance was assumed if $p < 0.008$.

Participant 1 Behavioural Performance

	Score	Time	10a0	10a5	Mm/s	Mm/s/250	Breach
Score	1	.083	.237**	.078	-.138	-.160	-.301**

**. Correlation is significant at the 0.007 level (2-tailed).

Table 4.5. The table exhibits the Pearson coefficient of the correlational analysis performed for Participant 1 between performance and the 6 indicators included in SCATT.

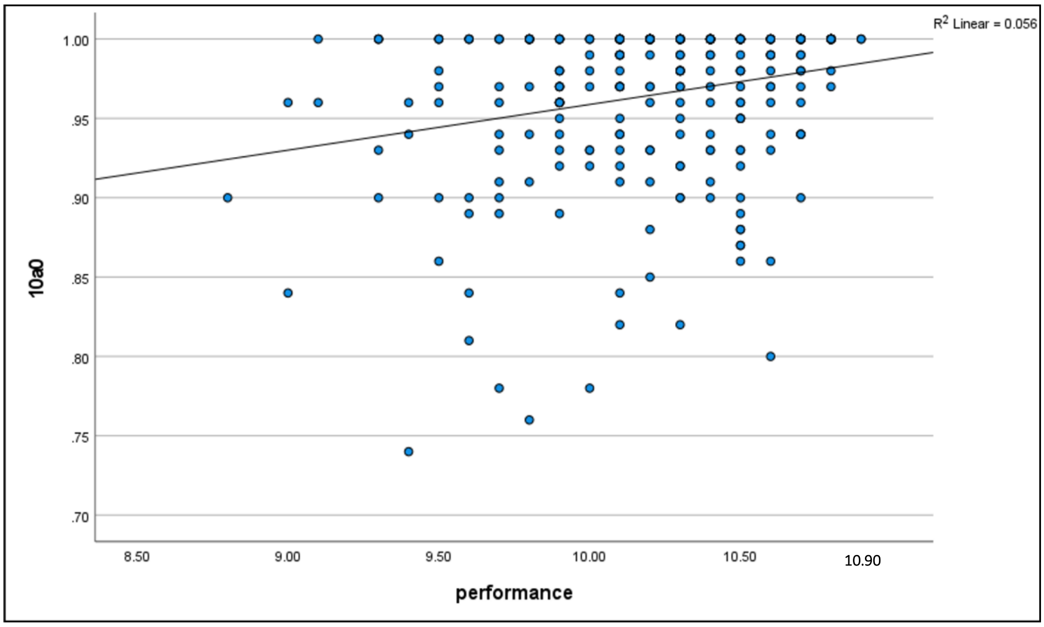


Figure 4.4. Relationship between performance and 10a0 indicator from the SCATT device.

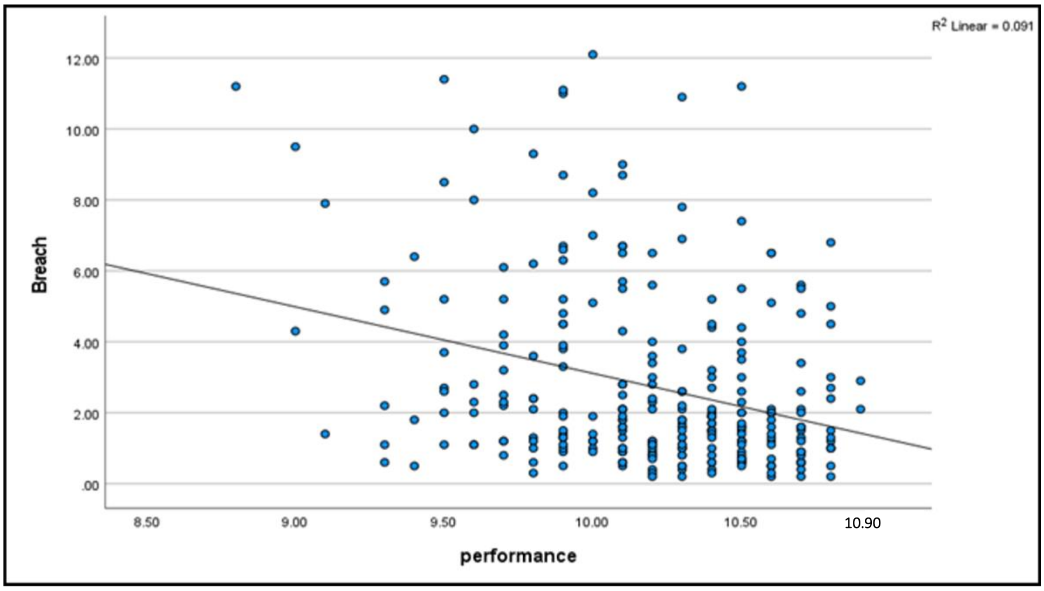


Figure 4.5. Relationship between performance and breach indicator from the SCATT device.

Table 4.5 exhibits the Pearson coefficient between performance (score) and indicators from the SCATT device for Participant 1. The data highlight two significant correlations, between performance and 10a0, and between performance and breach. The results from the Pearson correlation indicate a weak positive correlation between performance and stability (10a0) (r=.237, N=270, p<0.001). A scatterplot summarizing the results of the correlation is exhibited in Figure 4.4. The results from the correlation analysis indicate a weak relationship between the two variables, suggesting that the more stable the Air-Rifle barrel is throughout the last 3 seconds of the shot the higher the score. A negative moderate correlation has been found between performance and breach (r= -.301, N= 270, p<0.001). Figure 4.5 summarizes the results of the correlational analysis, indicating that the shorter the distance from the centre of the aim in the last three seconds of the shot the higher the score.

Participant 2 Behavioural Performance

	Score	Time	10a0	10a5	Mm/s	Mm/s/250	Breach
Score	1	-.108	.176	.088	-.138	-.159	-.234**

**. Correlation is significant at the 0.007 level (2-tailed).

Table 4.6. The table exhibits the Pearson coefficient of the correlational analysis performed for Participant 2 between performance and the 6 indicators included in SCATT.

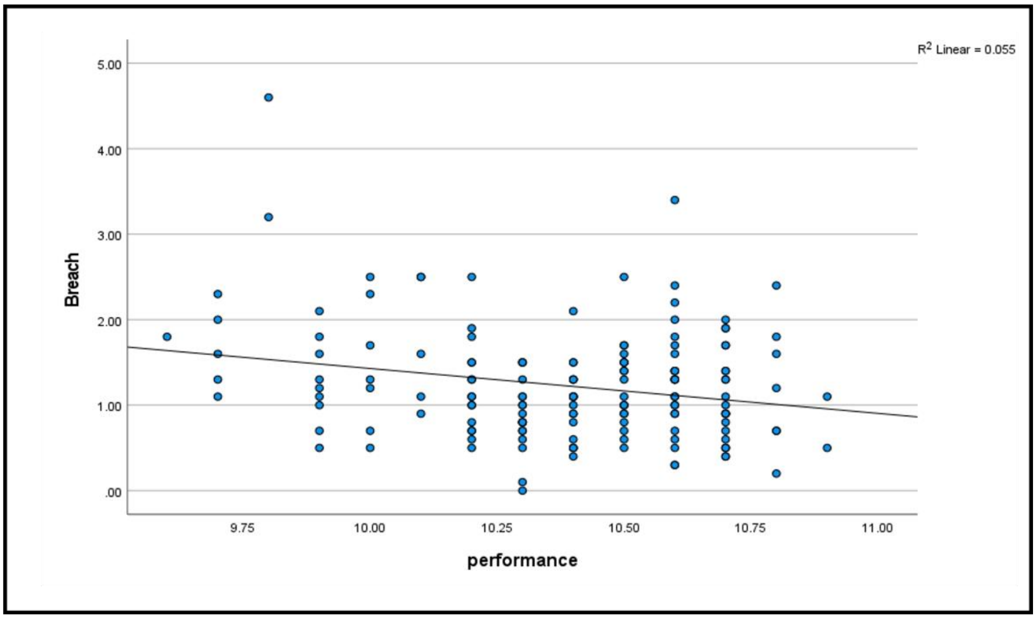


Figure 4.6. Relationship between performance and breach indicator from the SCATT device for participant 2.

Table 4.6 exhibits the Pearson coefficient between performance (score) and indicators from the SCATT device for Participant 2. The results from the correlational analysis indicate a negative weak correlation between performance and breach (r= -.234, N= 160, p<0.001). The scatterplot exhibited in Figure 4.6 summarizes the results of the correlational analysis, indicating that shorter distances from the centre of the target in the last three seconds of the shot results in higher scores.

4.6.1 EEG Analysis

4.6.1.1 Root Mean Square (RMS)

To calculate the Root Mean Square (RMS) each trial, for each participant, for each session was averaged and created for each condition. Based on the results presented in Figure 4.7 the means between both conditions (successful and unsuccessful) do not differ in the baseline period across sessions, suggesting that any neural effects found across conditions are not a result of variance in the signal quality due to the selection of the baseline in Participant 1.

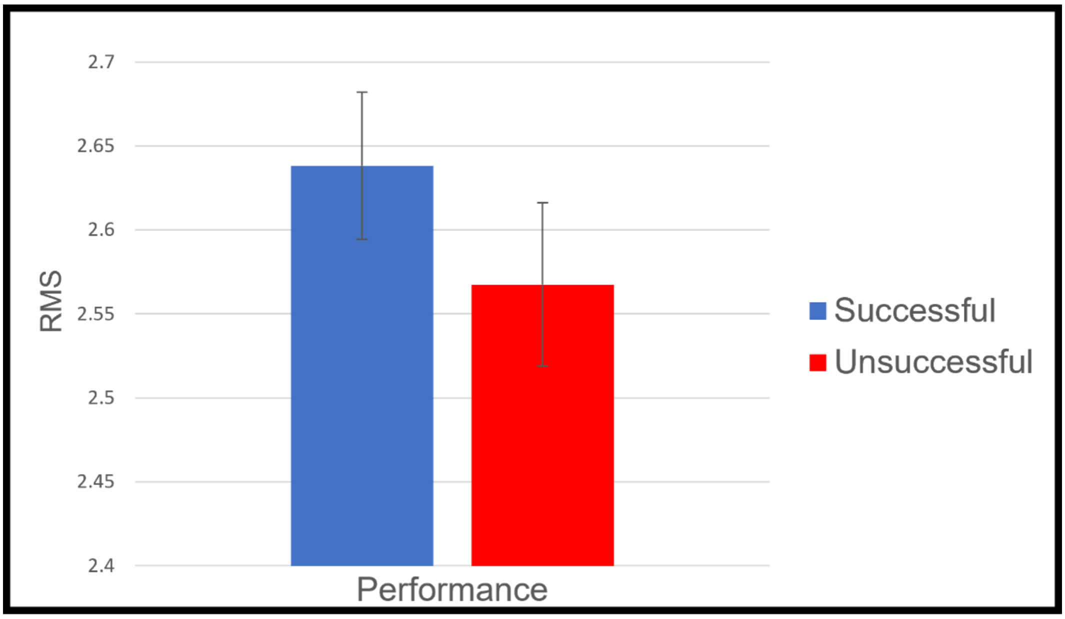


Figure 4.7. Root Mean Square of the baseline period (-15000ms to -14000ms) recorded at all electrodes of interest in Participant 1 across all sessions for successful (blue) and unsuccessful (red) performance.

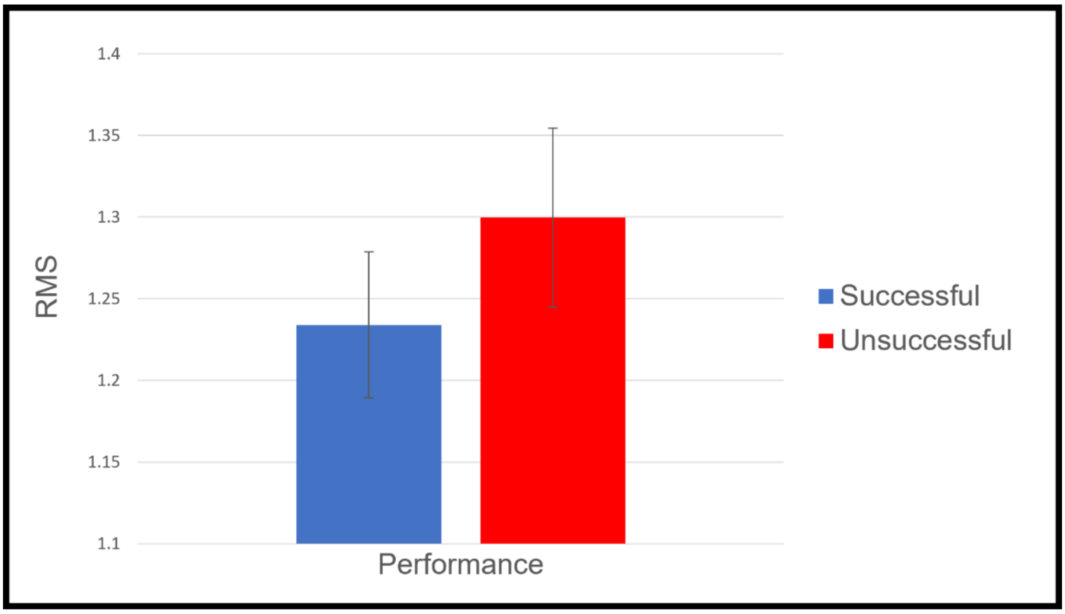


Figure 4.8. Root Mean Square of the baseline period (-12000ms to -11000ms) recorded at all electrodes of interest in Participant 2 across all sessions for successful (blue) and unsuccessful (red) performance.

Based on the data presented in Figure 4.8 the means between successful and unsuccessful performances in the baseline period for Participant 2 do not differ, suggesting that any neural effects found across conditions are not a result of variance in the signal quality due to the selection of the baseline in Participant 2.

4.6.1.2 Participant 1

4.6.1.3 *Time-Frequency analysis*

To provide an overview of changes in power throughout the pre-shot period a series of time-frequency plots were generated for Participant 1, characterising the pattern of effects for successful and unsuccessful performance. Individual time-frequency plots are provided for frontal, central, parietal, and occipital regions to illustrate how variable the pattern of power is across the scalp. Before presenting the outcomes of statistical analysis using 95% confidence intervals focused on each frequency band, we first describe the pattern of effects that is shown in the time-frequency plots.

Frontal Region

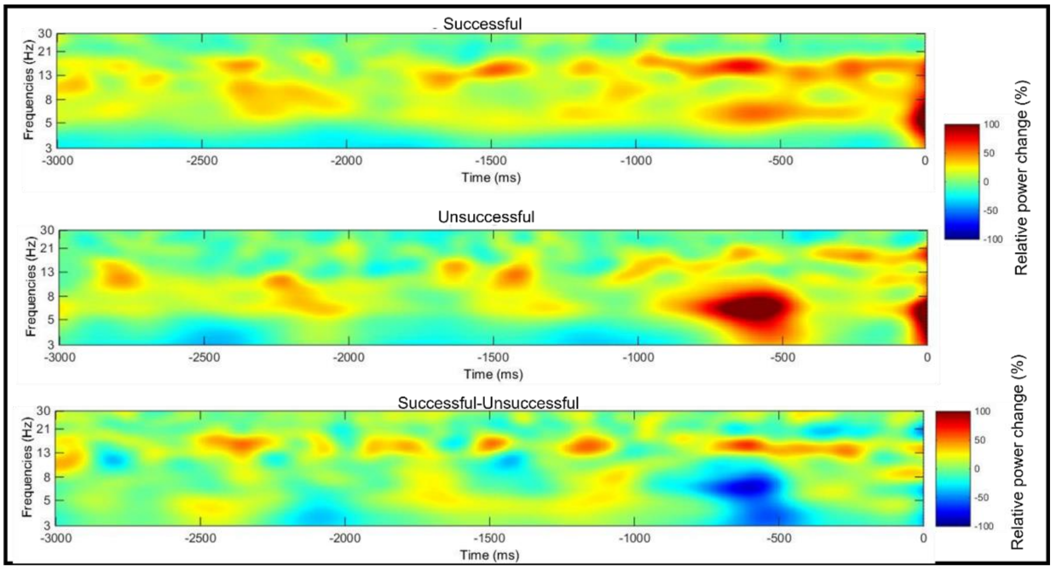


Figure 4.9. The time frequency plots exhibit the neural activity across frequencies in the three second time-period of interest at the frontal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.9 illustrates changes in power across all frequency bands for successful compared to unsuccessful performance over the pre-shot period, averaged across a set of frontal electrodes (F3/Fz/F4). A clear peak of theta (4-7Hz) and alpha (8-12Hz) power is present for unsuccessful performance during the third time window (-1000ms to 0). Short-lived bursts of power are evident across time within the SMR (13-15Hz) and beta power (15-30Hz) most pronounced for successful performance.

Central Region

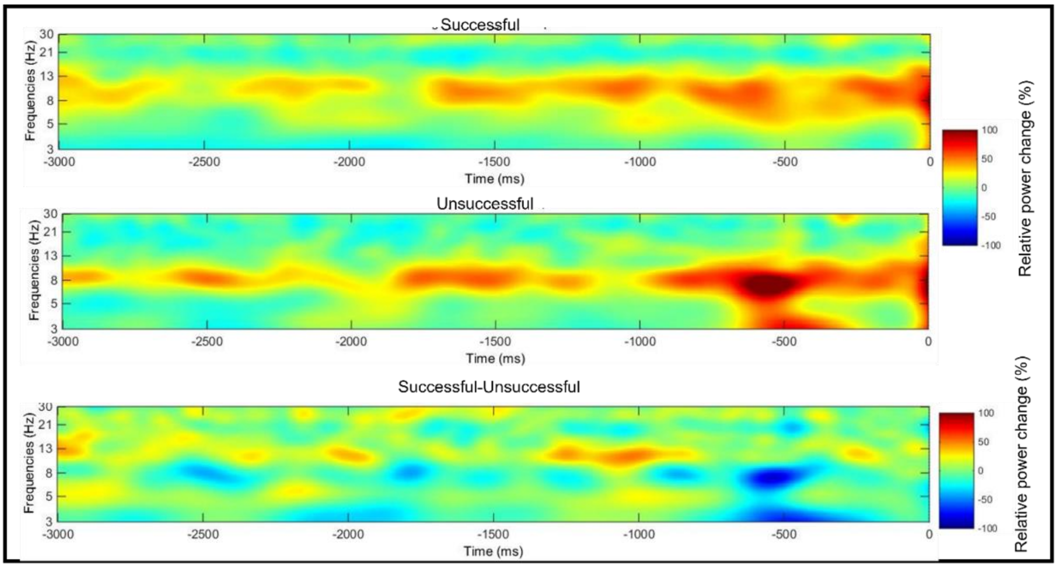


Figure 4.10. The time frequency plots exhibit the neural activity across frequencies in the three second time period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.10 illustrates changes in power across all frequency bands averaged across a set of central electrodes (C3/Cz/C4). In comparison to the effects seen over frontal electrodes there is a continuous increase of alpha (8-12Hz) power over central electrodes during all time windows, with a clear peak of theta (4-7Hz) and alpha power (8-12Hz) during the third time window most pronounced for unsuccessful performance. As is evident in the difference plot, however, the increases underlying unsuccessful performance are most pronounced within time window 3.

Parietal Region

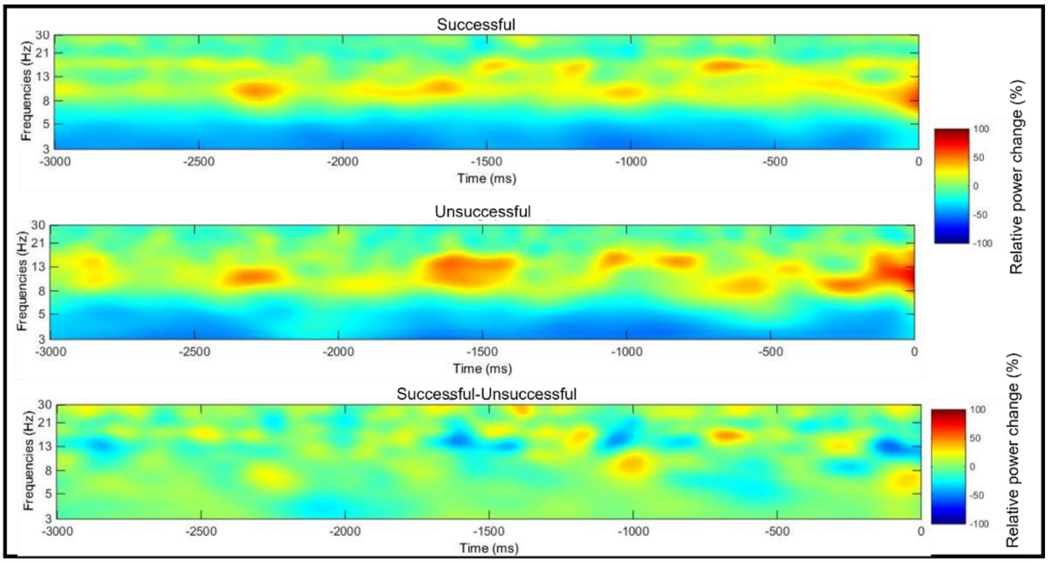


Figure 4.11. The time frequency plots exhibit the neural activity across frequencies in the three second time period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.11 illustrates changes in power averaged across a set of parietal electrodes (P3/Pz/P4). An increase in SMR power (13-15Hz) can be seen underlying unsuccessful performance during time window 2.

Occipital Region

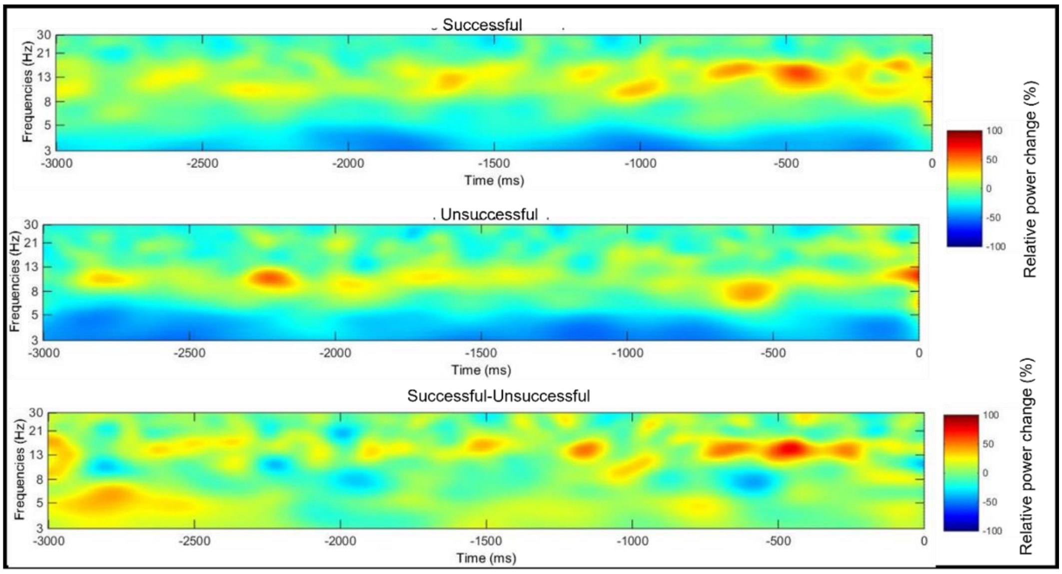


Figure 4.12. The time frequency plots exhibit the neural activity across frequencies in the three second time period of interest at the occipital region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.12 illustrates the pattern of power at occipital electrodes (O1/Oz/O2). Successful performance is associated with a short-lived increase in theta (4-7Hz) during time window 1 as evident in the difference time frequency plot. Short live bursts of power are present for SMR power (13-15Hz) during the third time window (-1000ms to 0) underlying successful performance.

Taken together, the time-frequency plots suggest that there are marked changes in brain power for both successful and unsuccessful performance for Participant 1. To further examine the pattern of results as planned, below the data are analysed using the 1 second time windows typically reported in prior literature.

4.6.1.3.1 Alpha Frequency (8-12Hz)

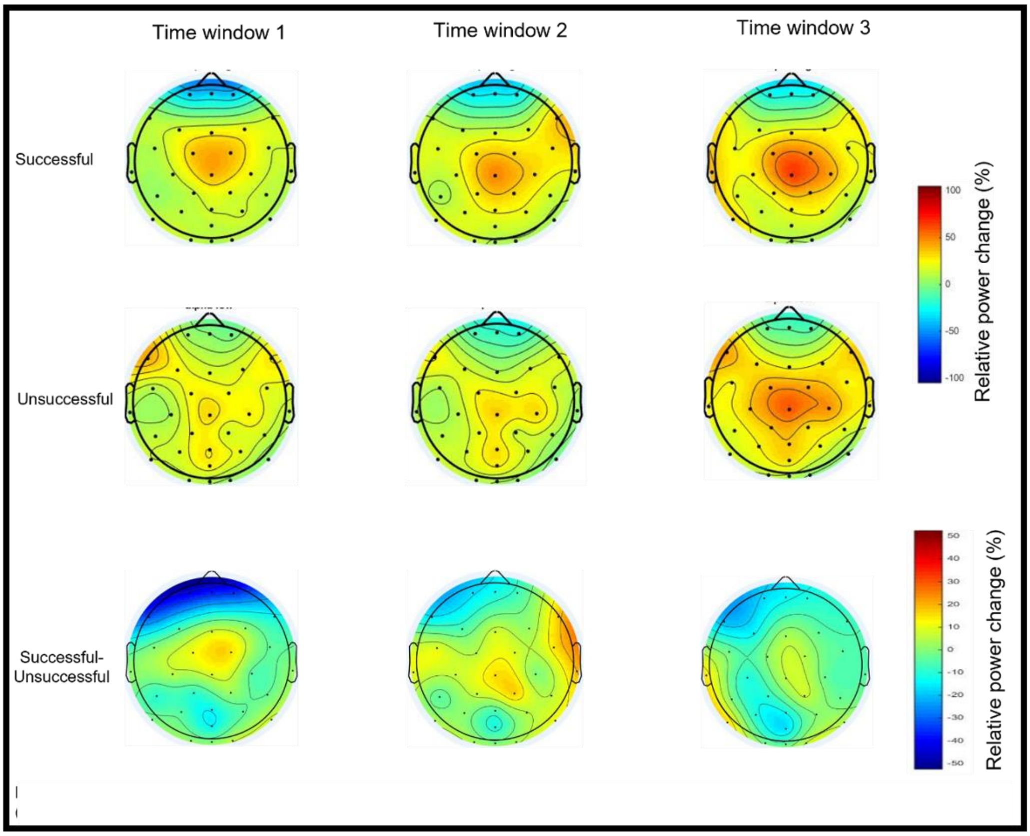


Figure 4.13. The scalp maps represent alpha activity (8-12Hz) at the all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.13, there is a focal increase of alpha power over fronto-central electrodes, which is more evident in successful performance during all time windows. Additionally, there is less alpha power underlying successful performance over parietal electrodes compared to unsuccessful performance. The pattern of alpha power is not significantly different in the two levels of performance; this can also be seen in Figure 4.14, which displays the mean power and confidence intervals (95%) over all electrodes of interest across all three-time windows.

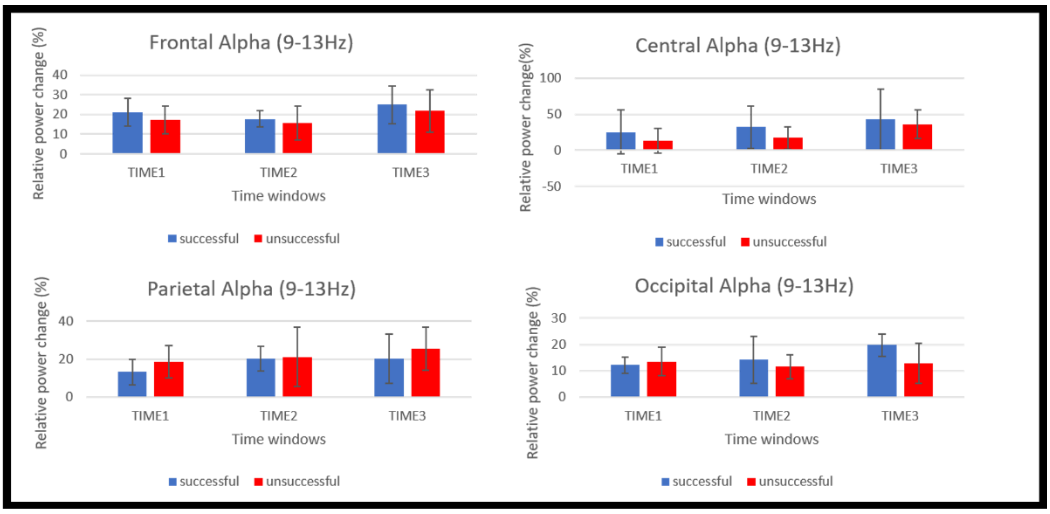


Figure 4.14. The figure exhibits the alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

In the section below alpha was investigated separately for low- and high-alpha power and the pattern of power was examined for successful and unsuccessful performance, but no differences were found.

4.6.1.3.2 Low Alpha Frequency (8-10Hz)

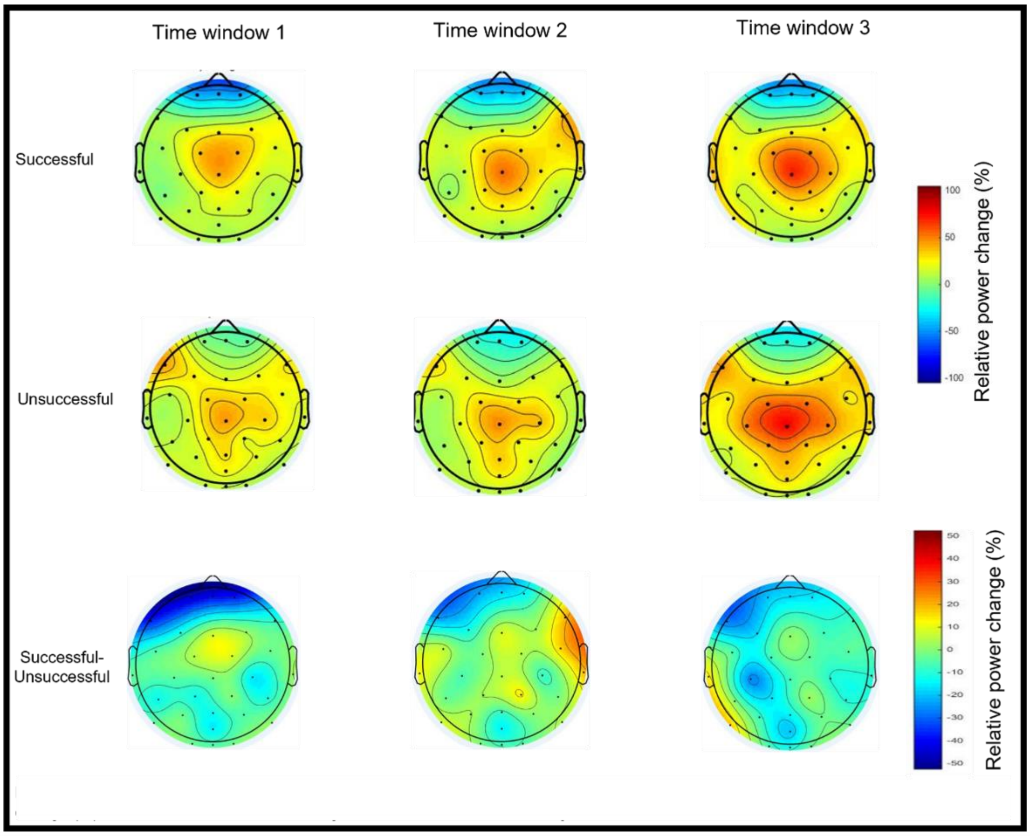


Figure 4.15. The figure represents the low alpha activity (8-10 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

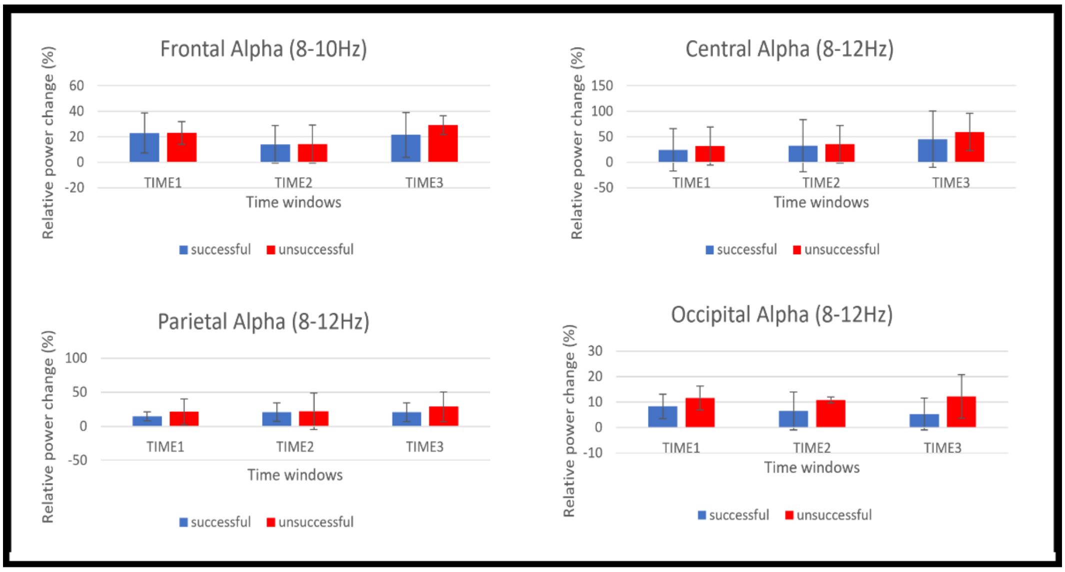


Figure 4.16. The figure exhibits the low alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.3 High Alpha Frequency (10-12Hz)

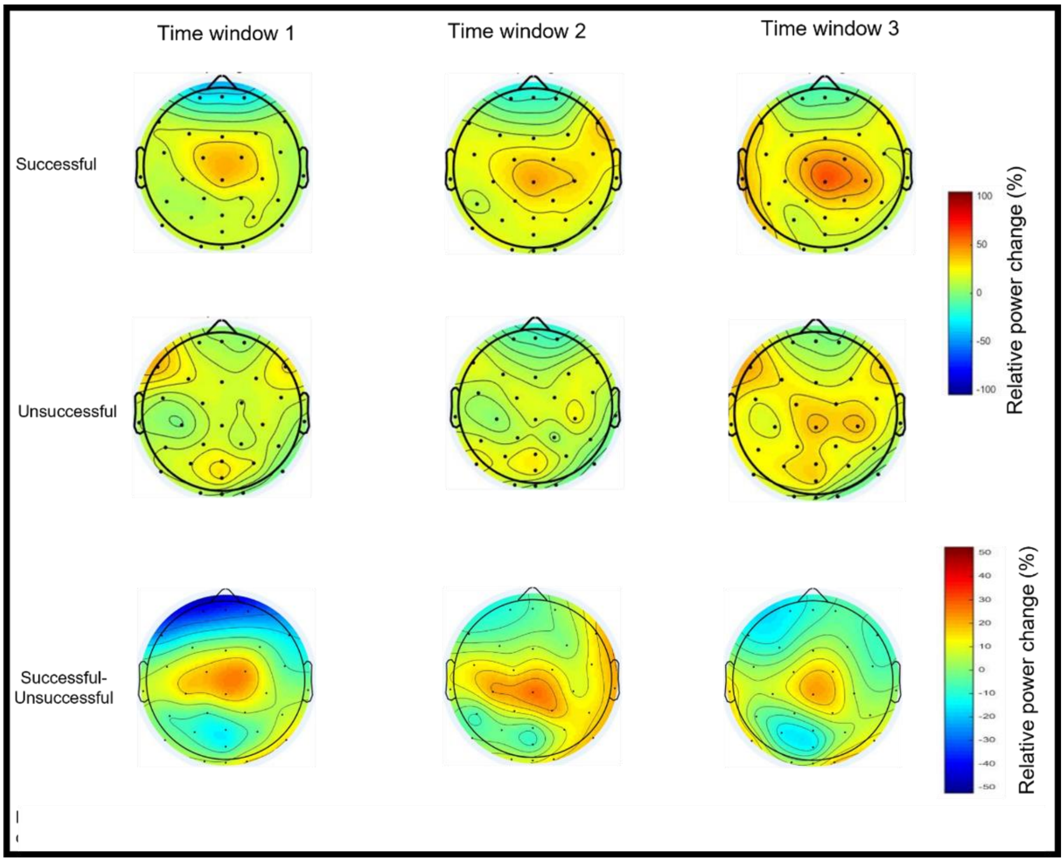


Figure 4.17. The figure represents the high alpha activity (10-12 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

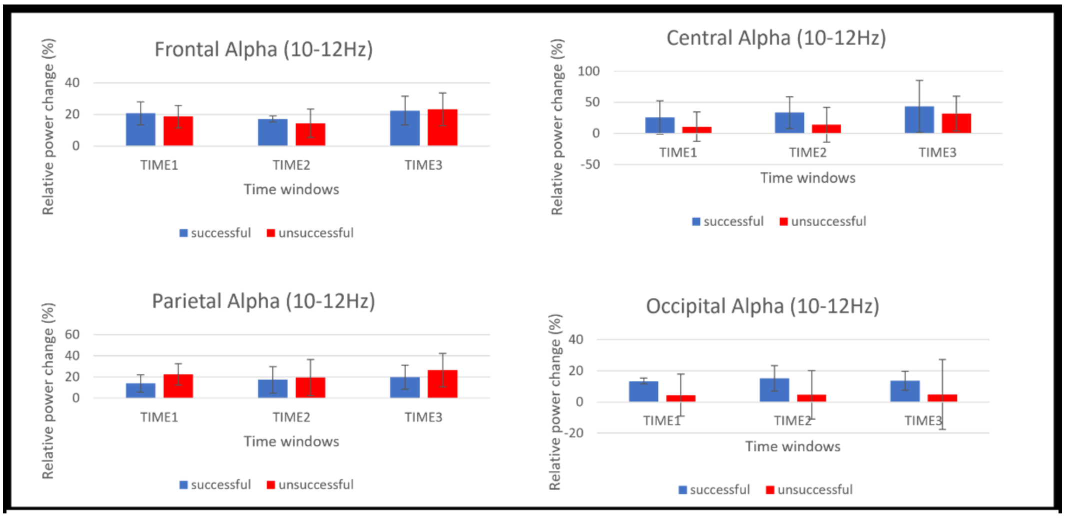


Figure 4.18. The figure exhibits the high alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

Additional Targeted Analysis for Alpha

Additional targeted analysis was conducted, focusing on electrodes FC1/Cz/FC2. As seen in Figure 4.19 (top), there was greater overall alpha power throughout the preparation period of a successful shot compared to an unsuccessful shot. Interestingly, different patterns of alpha power were revealed when looking separately at the low and high alpha sub-bands. More specifically, there was a clear increase in high alpha power before a successful shot, which was significantly different to the power prior to an unsuccessful shot between 3000 to 2000ms prior to the shot. However, the reverse pattern was observed in the low alpha sub-band (i.e., significantly higher alpha power between 3000 and 2000ms prior to an unsuccessful shot), and no difference in the remaining preparation period.

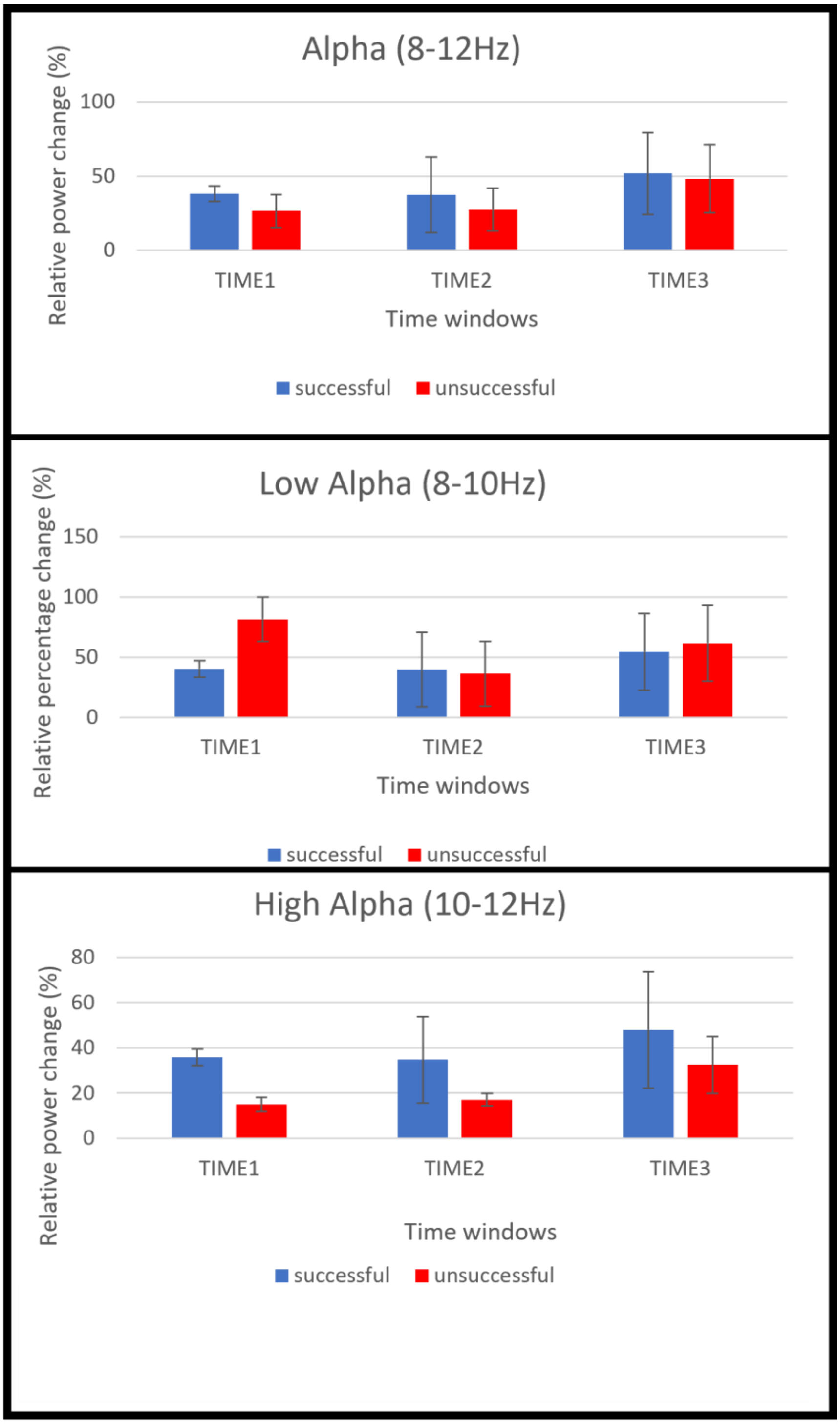


Figure 4.19. The figure exhibits the alpha, low- and high-alpha mean activity in percentage change for successful and unsuccessful performance at three-time windows Cz/FC1/FC2 electrodes. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.1 Individual Alpha Frequency (9-13Hz)

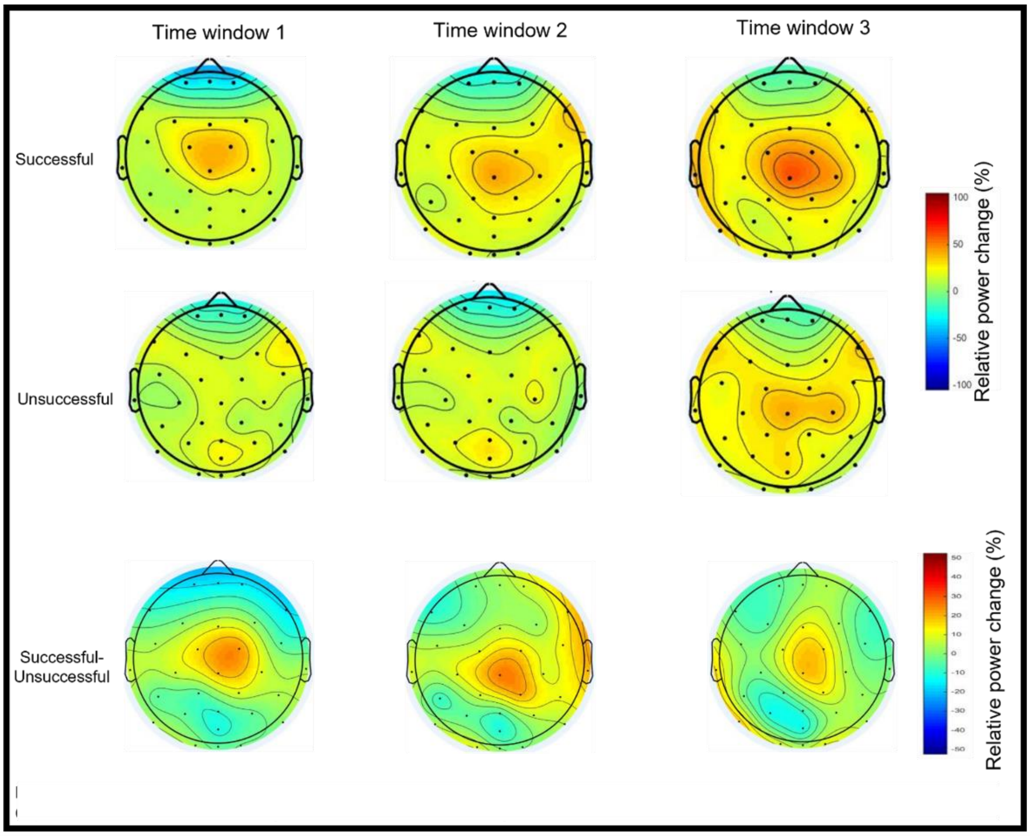


Figure 4.20. The figure represents the Individual Alpha Peak activity (9-13 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

The introductory section of this chapter argued the case for using individual alpha peak frequency to provide a better estimation of changes in alpha power. As outlined above, the individual alpha peak frequency for Participant 1 was estimated at 11Hz, thus an overall alpha frequency would range from 9-13Hz. As can be seen in Figure 4.20, there is a clear focal increase of alpha power over fronto-central areas during all time windows, which is more prominent for successful performance. This pattern is similar to the one observed with the use of *a-priori* defined alpha band of 8-12Hz. Furthermore, and similar to the *a-priori* alpha band, there was no significant difference between successful and unsuccessful performance and alpha power. Mean power and confidence interval (95%) error bars suggest that there is no reliable difference in overall alpha power underlying successful/unsuccessful performance for alpha and the separate alpha sub-bands.

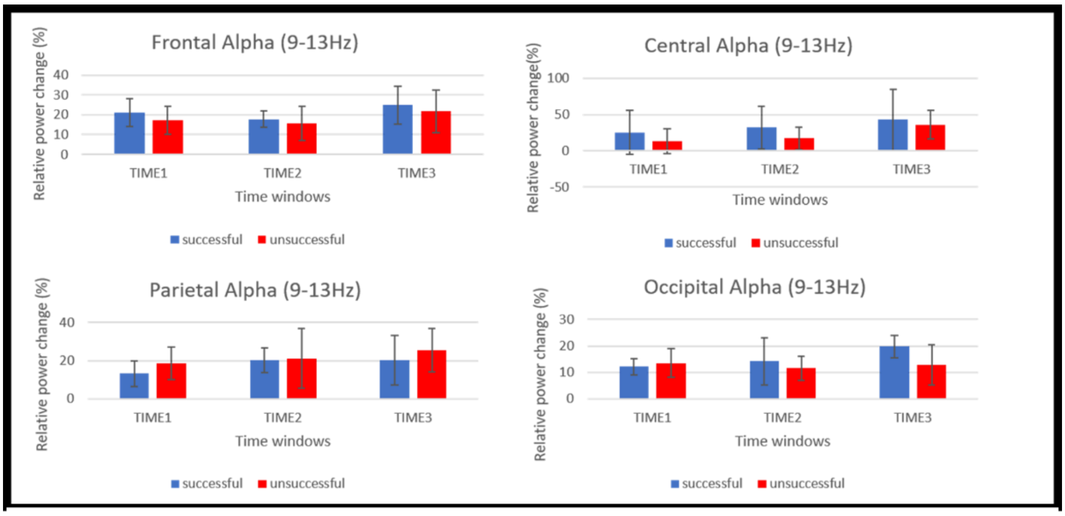


Figure 4.21. The figure exhibits the low alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.2 Low Alpha (9-11Hz)

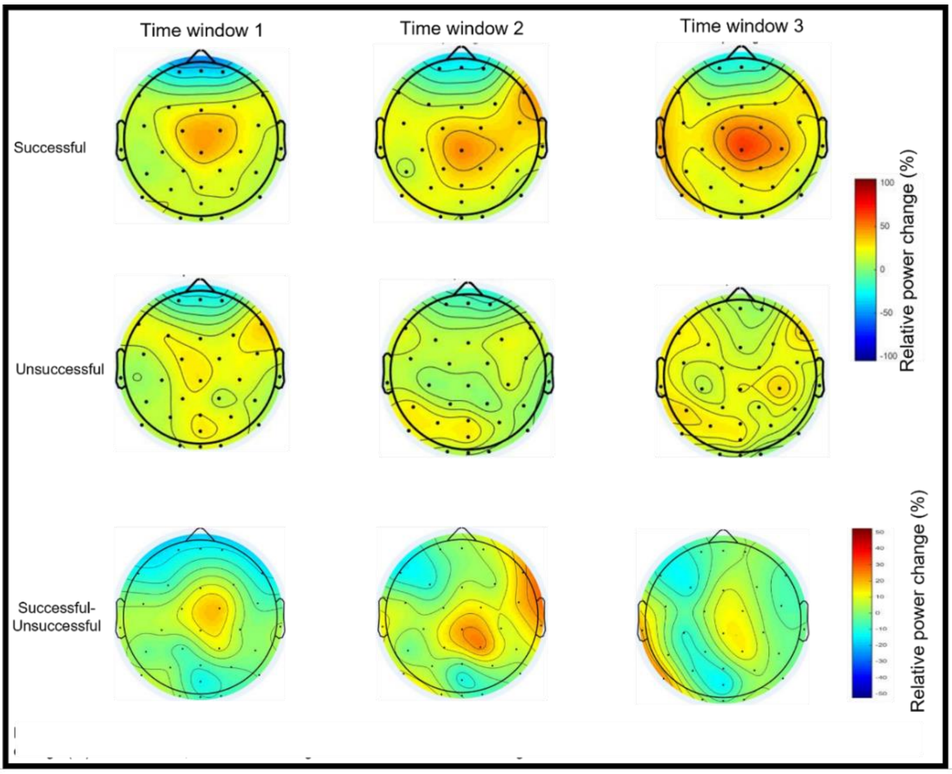


Figure 4.22. The figure represents the Individual Alpha Peak low activity (9-11 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.22, there is a clear focal increase of alpha power underlying successful performance during all time windows; by contrast, no low alpha power is visible during the time windows for unsuccessful performance. This difference is further illustrated in the scalp maps depicting the difference in low alpha power between (successful and unsuccessful performance). Assessment of the means and CIs suggest however, that the contrasting pattern depicted in the scalp maps underlying successful and unsuccessful performance is not significantly different as shown in Figure 4.23.

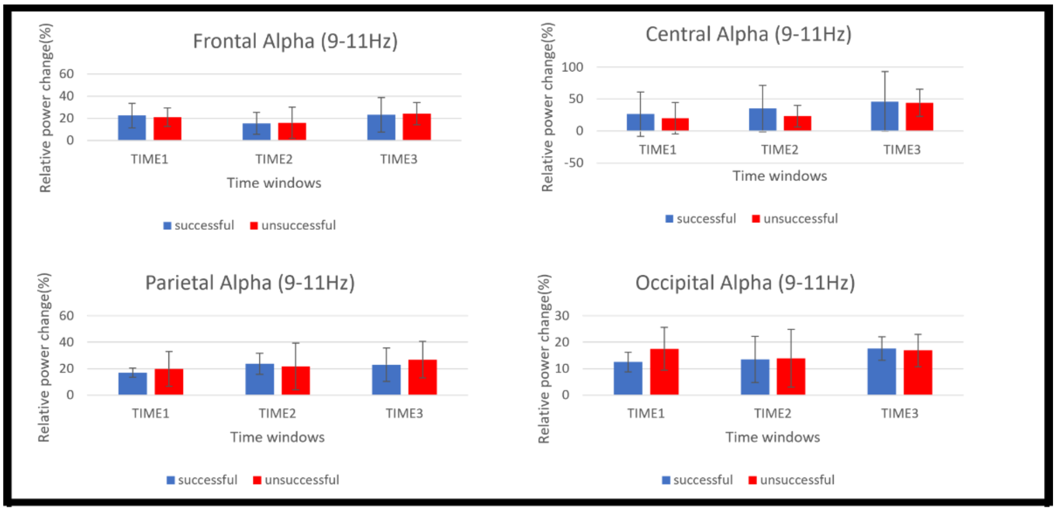


Figure 4.23. The figure exhibits the low alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.3 High Alpha (11-13Hz)

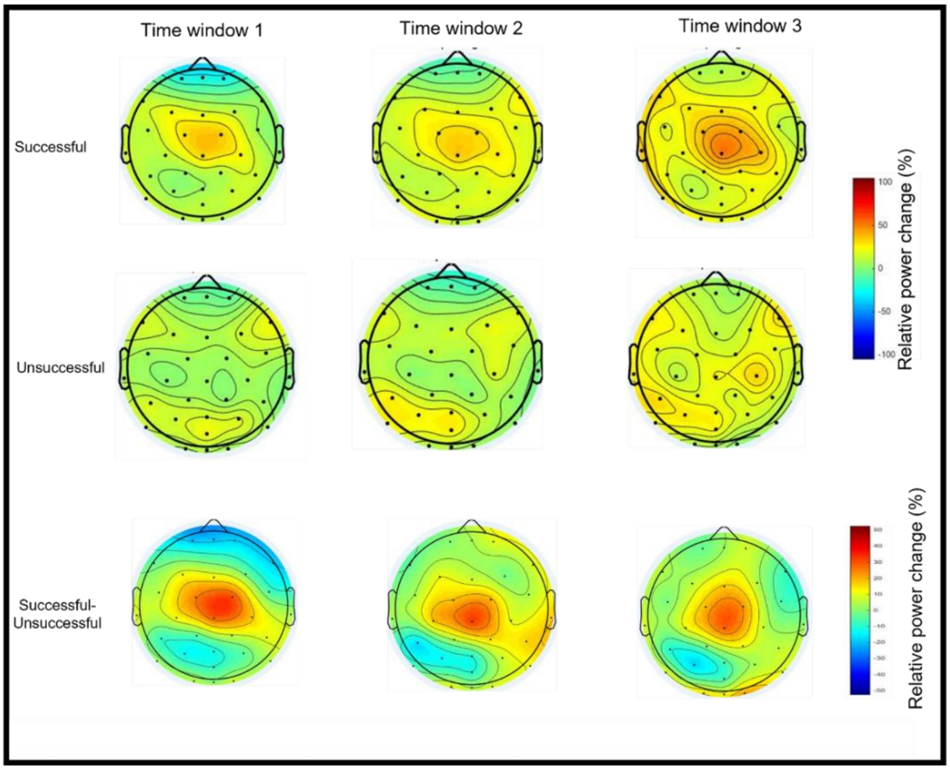


Figure 4.24. The figure represents the Individual Alpha Peak high activity (11-13 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Figure 4.24 presents the topographical maps for high alpha (11-13Hz) power for successful and unsuccessful performance. The pattern of power is very similar to the one in low alpha, but the difference between successful and unsuccessful performance is more prominent within the high alpha power (see scalp maps of the difference, Figure 4.24). However, even though an observable pattern is present underlying successful compared to unsuccessful performance, assessment of the 95% Cis suggest that the differences are not statistically reliable, as reflected in Figure 4.25.

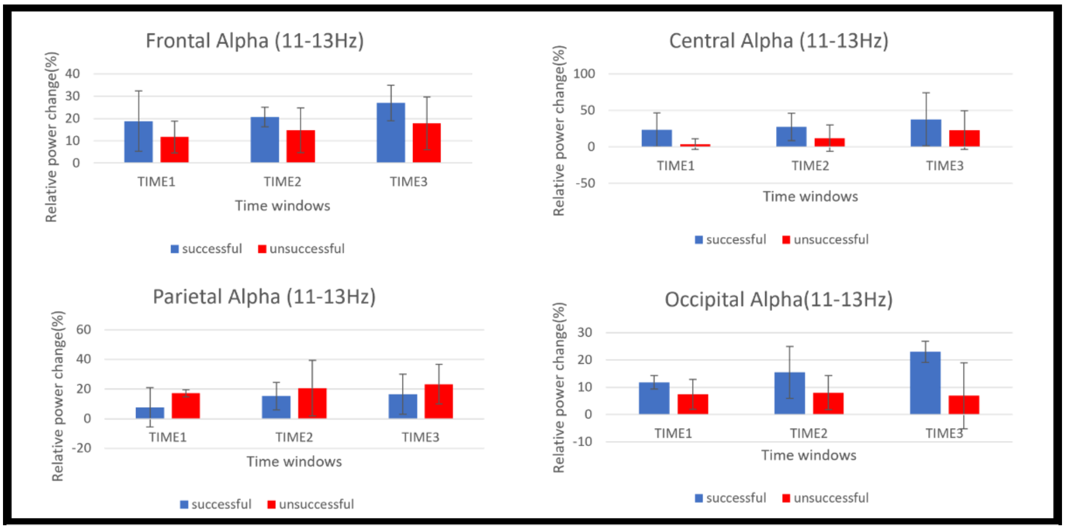


Figure 4.25. The figure exhibits the low alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

Additional Targeted Analysis Alpha Frequency (9-13Hz)

Additional targeted analysis was conducted focusing on electrodes FC1, FC2 and Cz. As seen in Figure 4.26 there was greater alpha power preceding successful shots throughout the preparation period, but it was significantly different before unsuccessful shots only between 3000 to 2000ms prior to the trigger pull.

The same pattern was observed when looking separately at lower and higher alpha bands. However, the difference between the two conditions was significantly different only in the higher alpha band, albeit for a prolonged period of time, more specifically between 3000 to 1000ms prior to the trigger pull. Additional correlational analysis was performed to investigate the relationship between high individual alpha peak (11-13Hz) and performance (Appendix A) which has been identified as significant through the Cis analysis. No significant correlations were identified through the analysis.

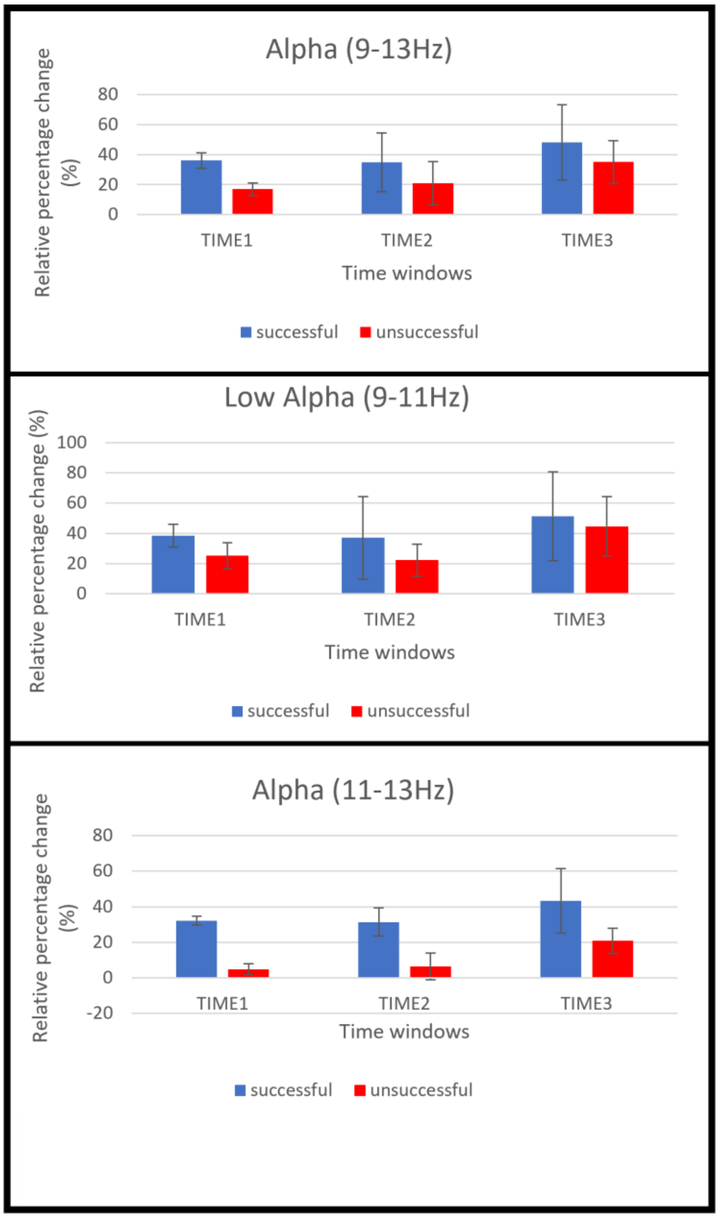


Figure 4.26. The figure exhibits the Individual Alpha Peak for alpha, low- and high-alpha mean activity in percentage change for successful and unsuccessful performance at three-time windows Cz/FC1/FC2 electrodes. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.4 Theta Frequency (4-7Hz)

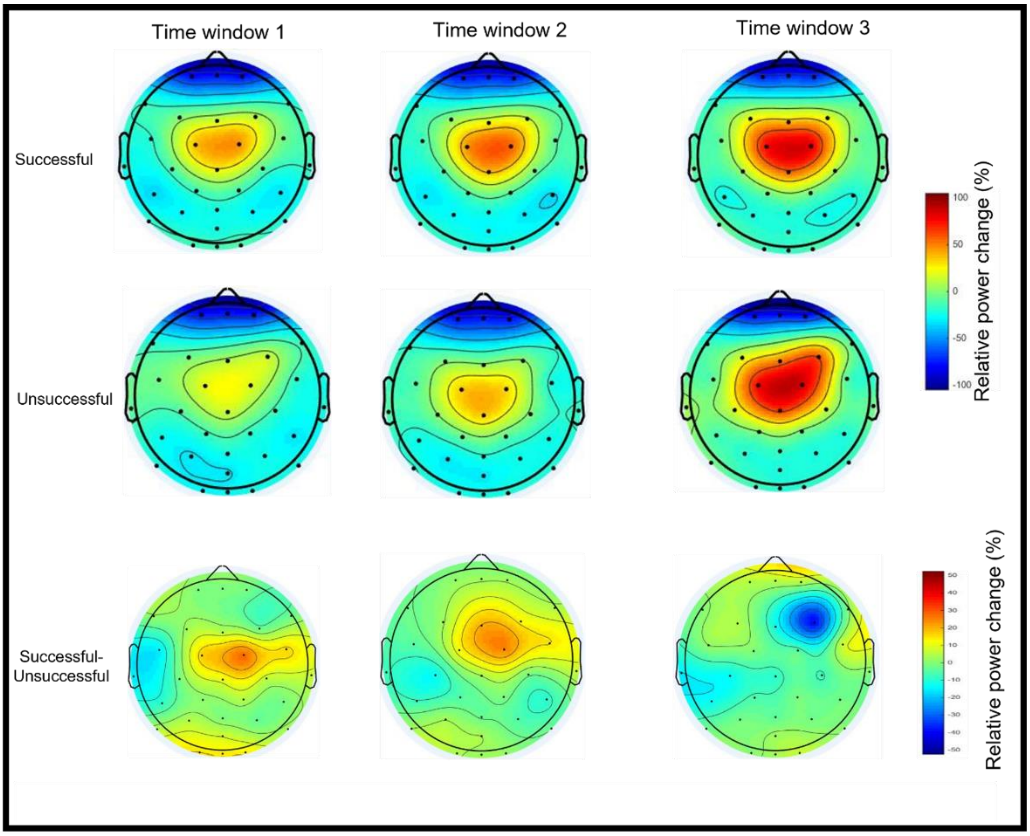


Figure 4.27. The figure represents the theta activity (4-7Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.27 there is a focal, fronto-central increase of theta power throughout the preparation period, the amplitude of which becomes progressively larger as the athlete gets closer to pulling the trigger. Interestingly, the amplitude of theta power seems to be larger before successful shots between 3000 to 1000ms before pulling the trigger compared to unsuccessful shots, but the pattern of the difference is reversed during the last 1000ms. The difference between the two conditions was quantified by pooling the theta power from electrodes FC1, FC2 and Cz (guided by the scalp maps, see Figure 4.27) in each of the time windows of interest; however, the difference between the two conditions failed to reach significance in theta power (Figure 4.28).

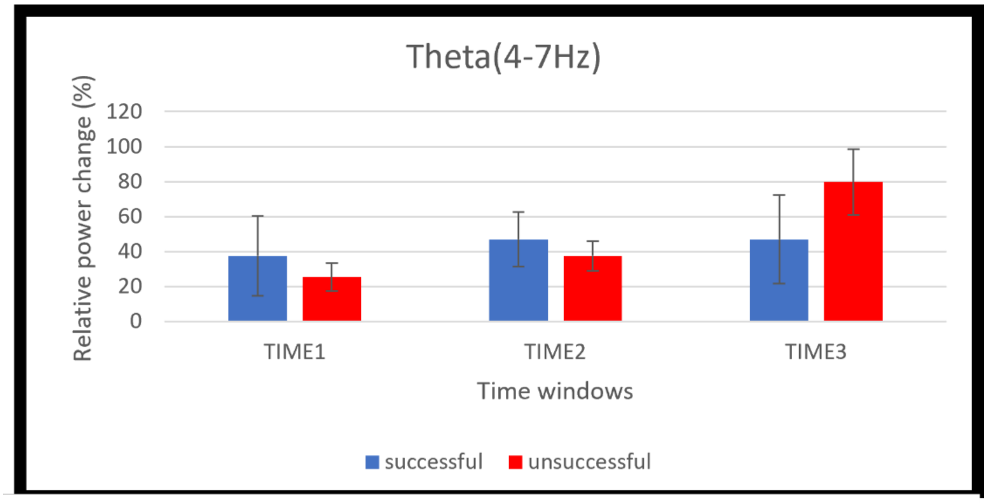


Figure 4.28. The figure represents the theta mean activity in percentage change for successful and unsuccessful performance across all time windows at FC1/FC2/Cz electrodes. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.5 Theta Frequency (5-9Hz)

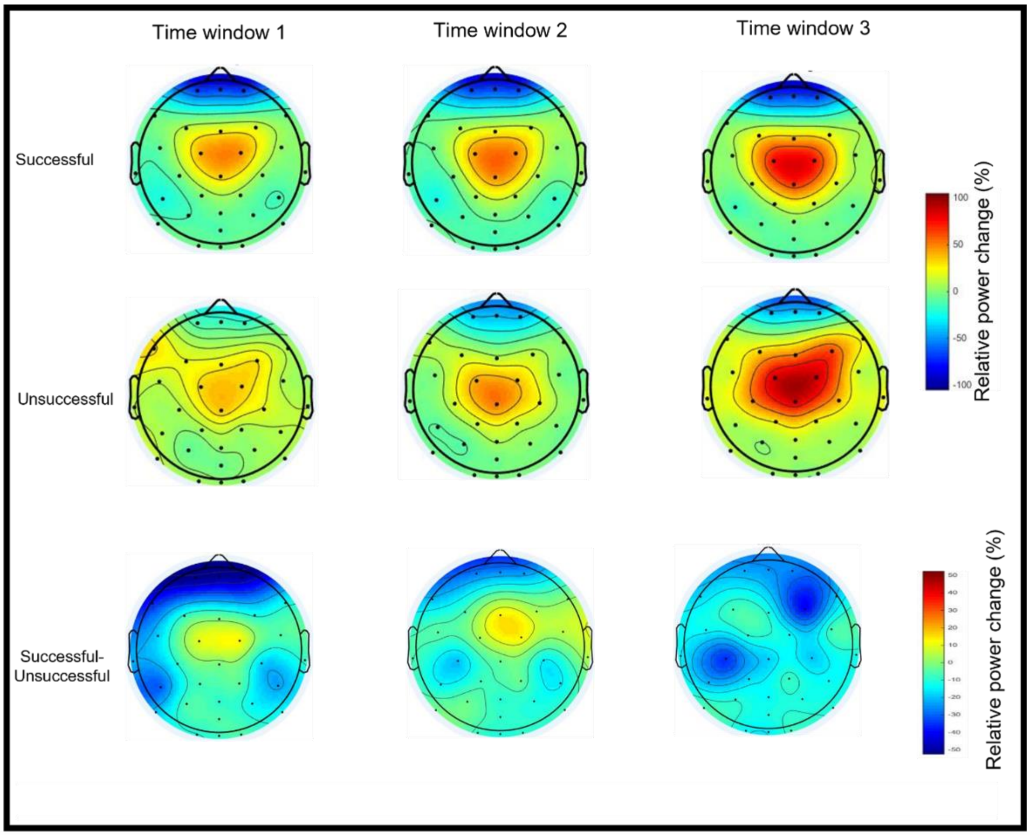


Figure 4.29. The figure represents the theta activity (5-8 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.29, the observed pattern of power for the individually adjusted theta, is similar to the one observed using the *a-priori* band. There is a fronto-central increase of theta power throughout the preparation period, the amplitude of which becomes progressively larger as the athlete gets closer to pulling the trigger. The difference between the two conditions was quantified by pooling the theta power from electrodes FC1, FC2 and Cz (guided by the scalp maps, Figure 4.29) in each of the time windows of interest. Once again, however, the difference between the two conditions failed to reach significance (Figure 4.30).

Figure 4.30. The figure represents the theta mean activity in percentage change for successful and unsuccessful performance across all time windows at FC1/FC2/Cz electrodes. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.6 Beta Frequency (15-30Hz)

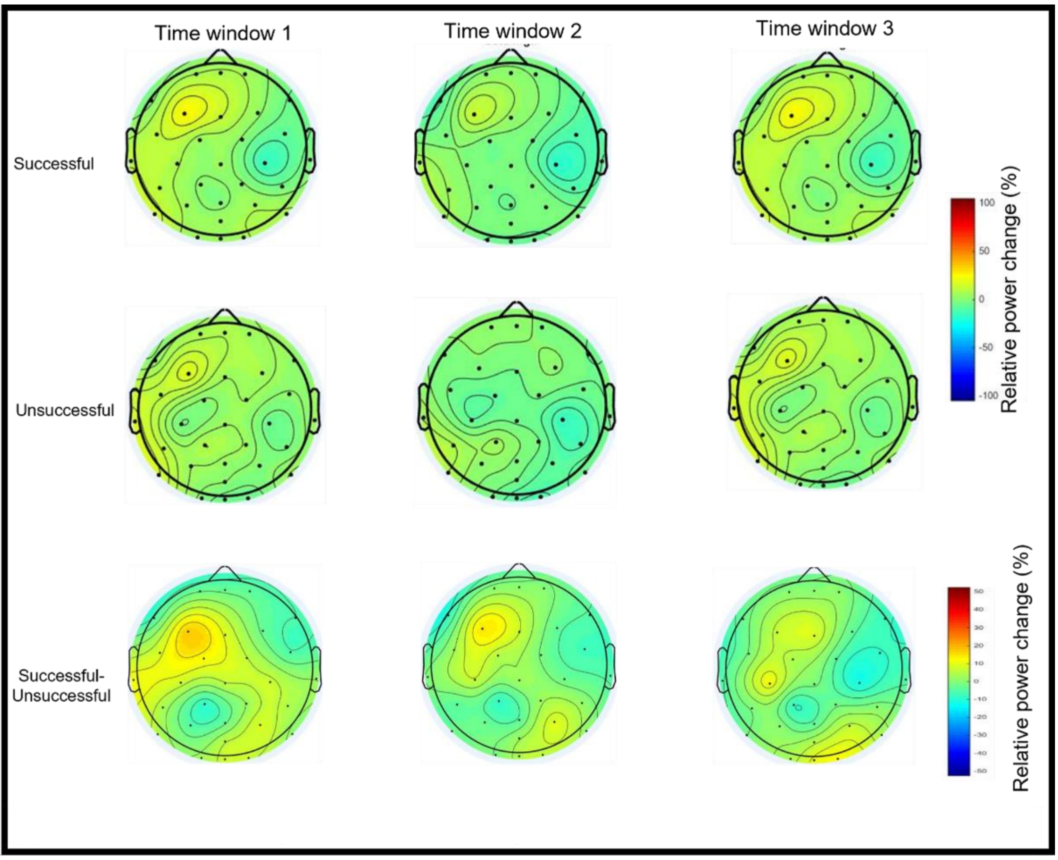


Figure 4.31. The figure represents beta activity (15-30 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.31 the topographic maps suggest that there are small differences in beta power underlying successful compared to unsuccessful performance. Successful shots are associated with an increase in beta over left frontal electrodes; the difference between successful and unsuccessful shots is more evident in time window 1 (-3000msto-2000ms) and time window 2 (-2000msto-1000ms). However, data analysis did not reveal any significant differences between the two levels of performance (Figure 4.32).

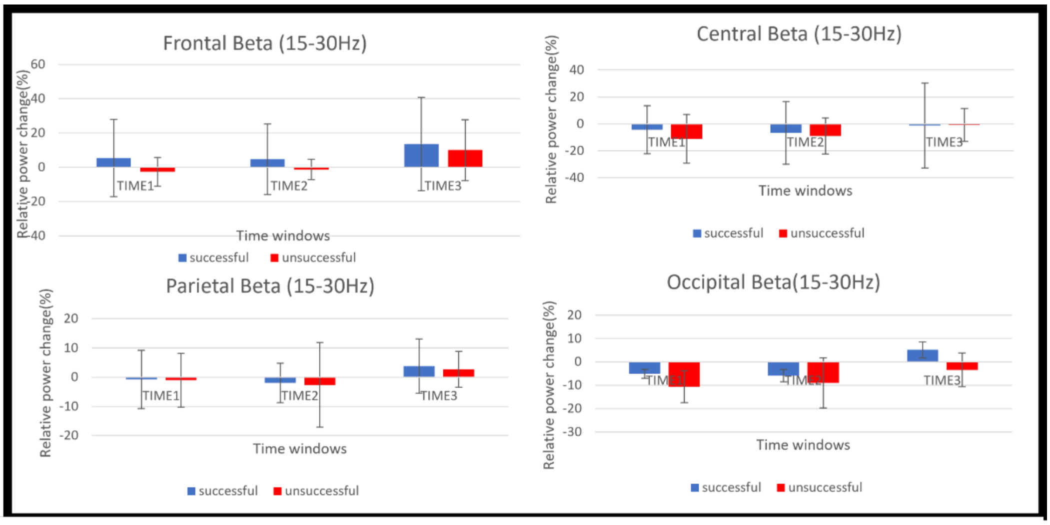


Figure 4.32. The figure represents the beta mean activity in percentage change for successful and unsuccessful performance across all time windows and across all regions of interest. The error bars represent the 95% confidence interval of the mean.

4.6.1.3.7 SMR Frequency (13 –15Hz)

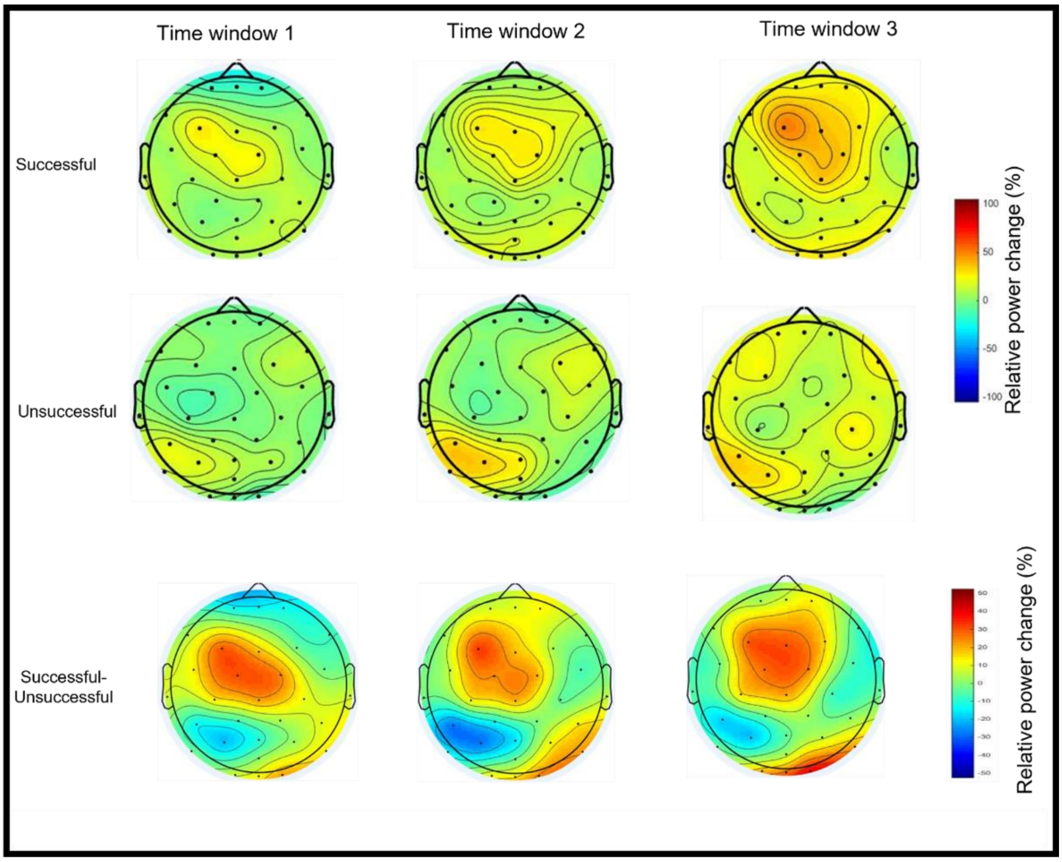


Figure 4.33. The figure represents SMR activity (13-15 Hz) at all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.33 there seems to be an increase of SMR power underlying successful compared to unsuccessful performance, evident in the topographic maps over frontal-central electrodes, appearing to be similar across all time windows. According to previous literature SMR power differences are prominent over the central electrodes (C3/Cz/C4). Here, however, there is no difference in the SMR underlying successful versus unsuccessful performance over the central region (as seen in Figure 4.34).

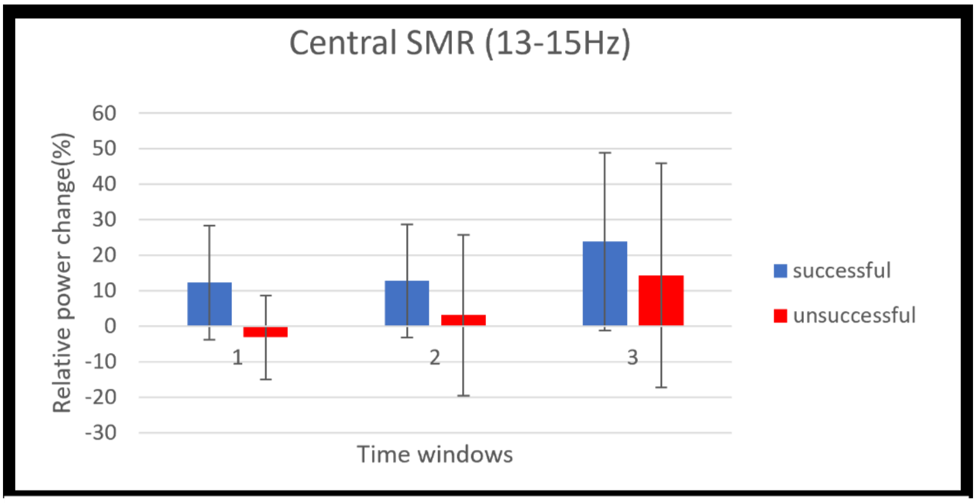


Figure 4.34. The figure represents the SMR mean activity in percentage change for successful and unsuccessful performance across all time at the central region. The error bars represent the 95% confidence interval of the mean.

4.6.1.4 Participant 2

4.6.1.5 *Time-Frequency analysis*

To provide an overview of changes in power throughout the pre-shot period a series of time-frequency plots were generated for Participant 2, characterising the pattern of effects for successful and unsuccessful performance. Individual time-frequency plots are provided for frontal, central, parietal and occipital regions to illustrate how variable the pattern of power is across the scalp. Before presenting the outcomes of statistical analysis using 95% confidence intervals focused on each frequency band, we first describe the pattern of effects shown in the time-frequency plots.

Frontal Region

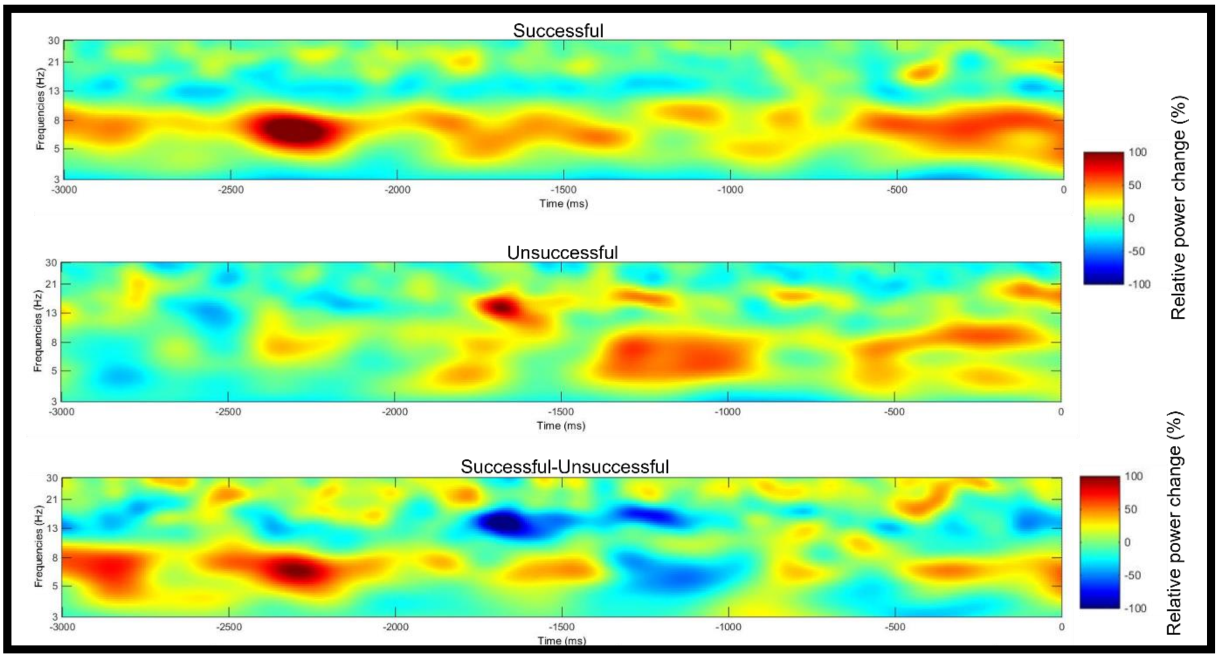


Figure 4.35. The time frequency plots exhibit the neural activity across frequencies in the three second time-period of interest at the frontal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.35 illustrates changes in power across all frequency bands for successful compared to unsuccessful performance over the pre-shot period, averaged across a set of frontal electrodes (F3/Fz/F4). The first two windows (-3000ms to 2000ms and -2000ms to -1000ms) exhibit short lived increases in theta (4-7Hz) and alpha (8-12Hz) power for successful performance. By contrast, during the third time window (-1000ms to 0ms) there appears to be a stronger increase in power for unsuccessful performance, initially exhibited in the SMR band (13-15Hz), followed by a clear peak in alpha power (8-12Hz).

Central Region

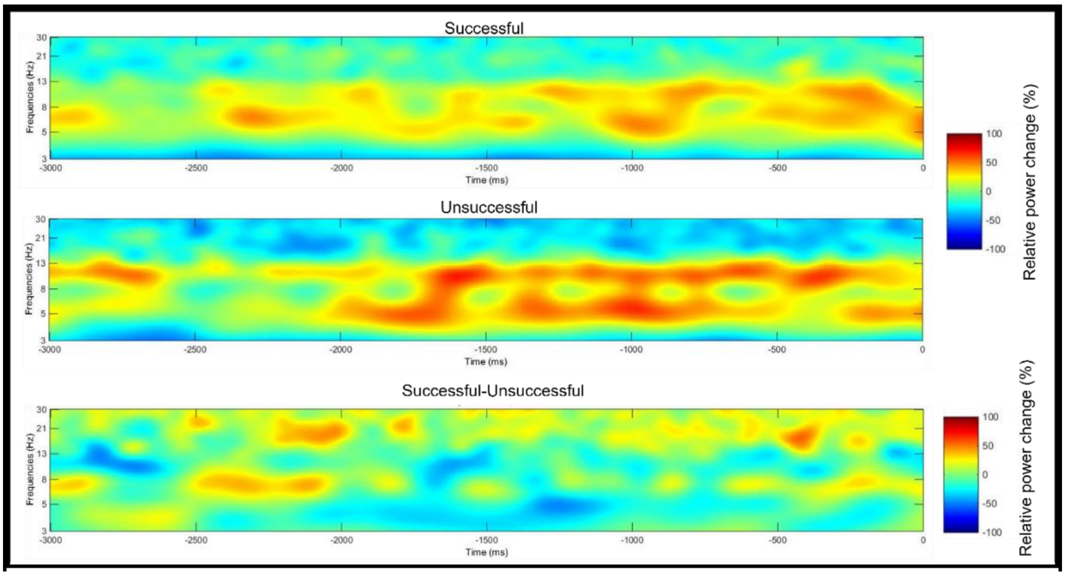


Figure 4.36. The time frequency plots exhibit the neural activity across frequencies in the three second time-period of interest at the central region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.36 illustrates changes in power across all frequency bands averaged across a set of central electrodes (C3/Cz/C4). In comparison to the effects seen over frontal electrodes there is a continuous increase of theta (4-7Hz) and alpha (8-12Hz) power over central electrodes during the second (-2000ms to -1000ms) and third (-1000ms to 0) time periods, and far less power throughout the pre-shot period over central electrodes underlying unsuccessful performance. As is evident in the difference plot, however, the increases underlying unsuccessful compared to successful performance are most pronounced within time window 2.

Parietal Region

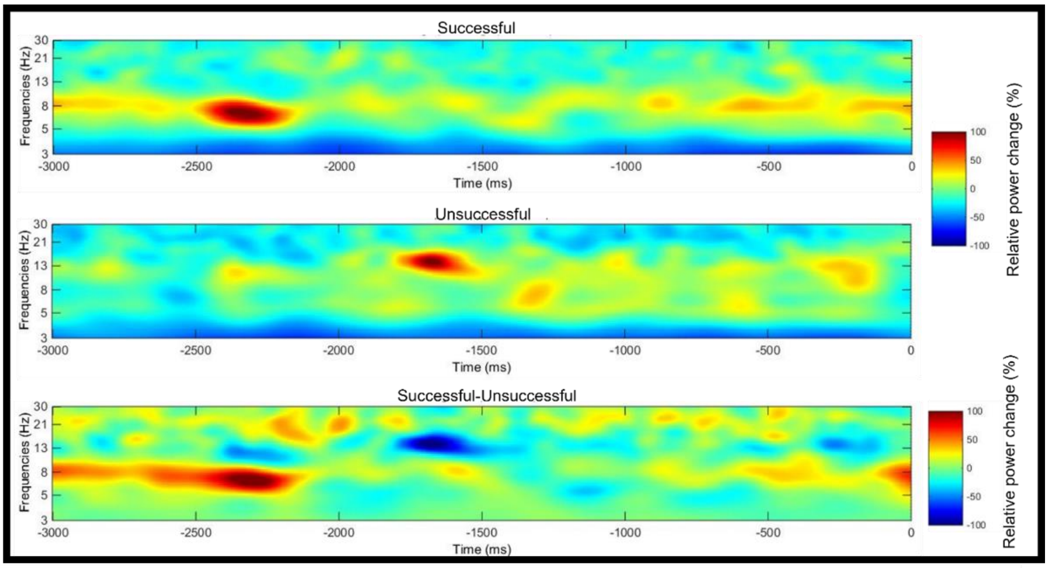


Figure 4.37. The time frequency plots exhibit the neural activity across frequencies in the three second time-period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.37 illustrates changes in power averaged across a set of parietal electrodes (P3/Pz/P4). Increases in theta (4-7Hz) and alpha (8-12 Hz) power are present for successful performance in time window 1 (-3000ms to -2000ms). An increase in SMR power (13-15 Hz) can be seen underlying unsuccessful performance during time window 2.

Occipital Region

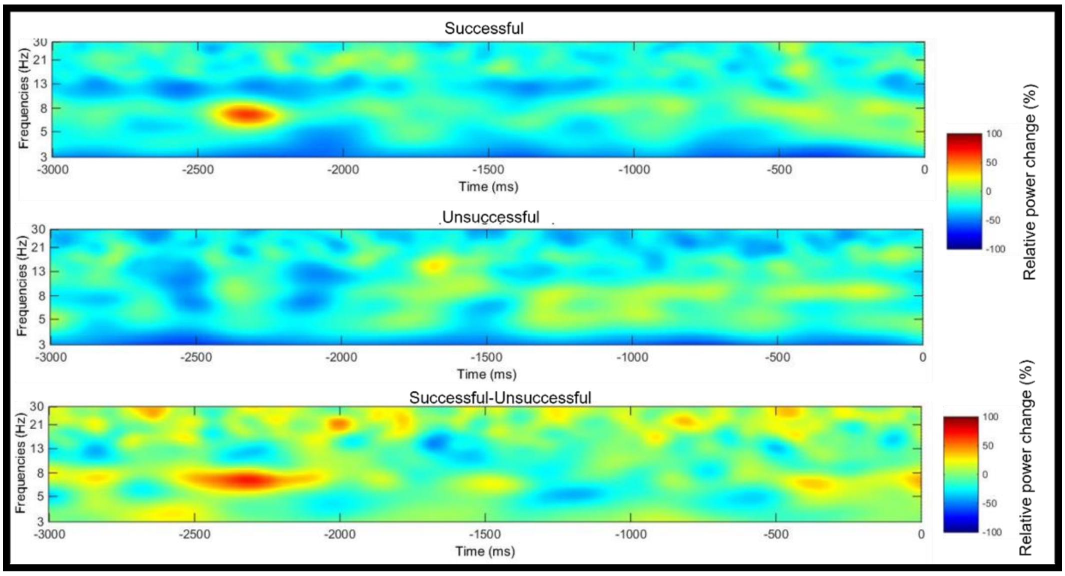


Figure 4.38. The time frequency plots exhibit the neural activity across frequencies in the three second time-period of interest at the parietal region. Zero indicates the time of the trigger pull. Successful and unsuccessful performance are exhibited in the first two plots, the third plot exhibits the difference of successful – unsuccessful. The scaling represents the relative power change (%) from baseline, with the red indicating an increase and blue indicating a decrease.

Figure 4.38 illustrates the pattern of power at occipital electrodes (O1/Oz/O2). Successful performance is associated with a short-lived increase in theta (4-7Hz) during time window 1, however, no other effects differentiating successful and unsuccessful performance are prominent.

Taken together, the time-frequency plots suggest that there are marked changes in brain power for both successful and unsuccessful performance for Participant 2. It is also evident that many of the differences in power are relatively transient, occurring briefly, rather than continuously throughout the epoch. Nonetheless, as planned, below the data are analysed using the 1 second time windows typically reported in prior literature.

4.6.1.5.1 Alpha Frequency (8-12 Hz)

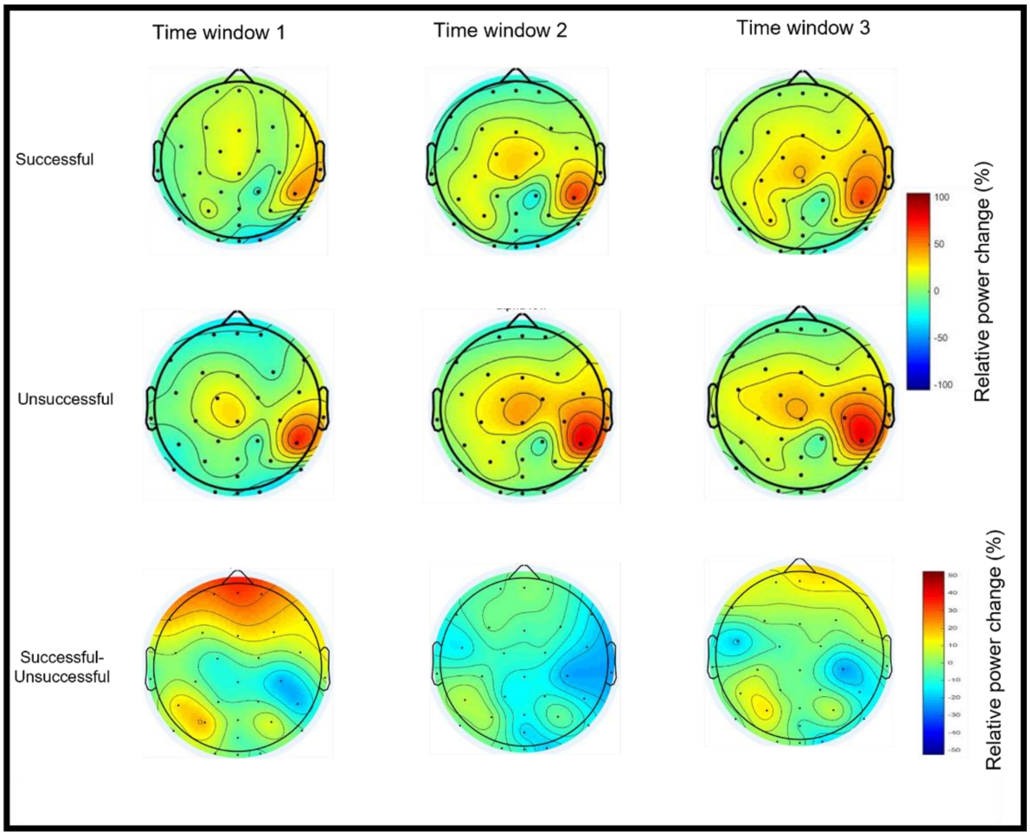


Figure 4.39. The scalp maps represent alpha activity (8-12Hz) at the all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.39, there is a focal increase in alpha power over the right centro-parietal areas, which is more pronounced in unsuccessful performance during all time windows. Additionally, there is less alpha power underlying successful performance over the central area compared to unsuccessful performance. Examination of the 95% Cis suggest however that the two levels of performance are not significantly different over all regions of interest and across all three-time windows (Figure 4.40).

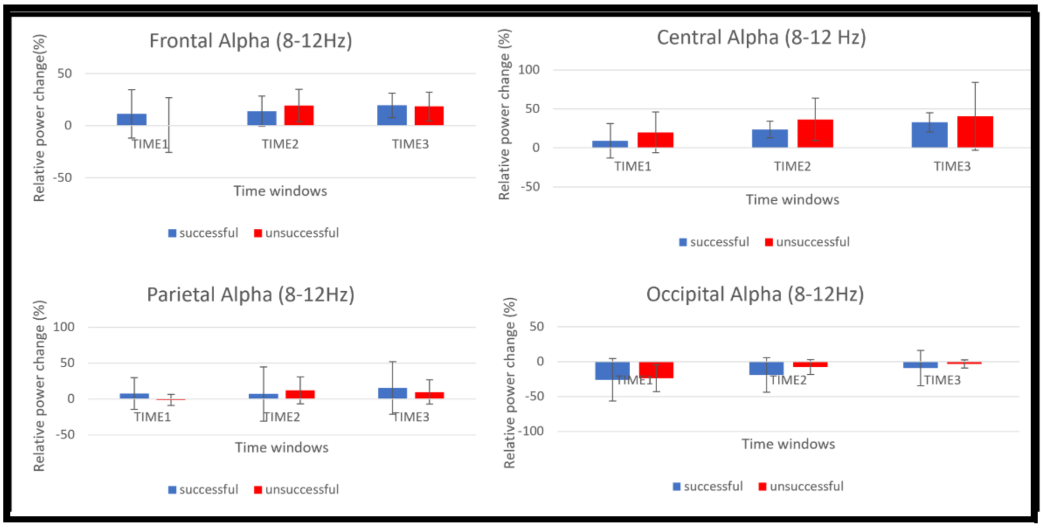


Figure 4.40. The figure exhibits the alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

For completeness, as planned, alpha power was investigated for low- and high- alpha sub-bands in the section below. As can be seen from Figures 4.41 and 4.42 (low alpha), and 4.43 and 4.44 (high alpha) no differences were present for either of the alpha sub-bands.

4.6.1.5.2 Low Alpha (8-10Hz)

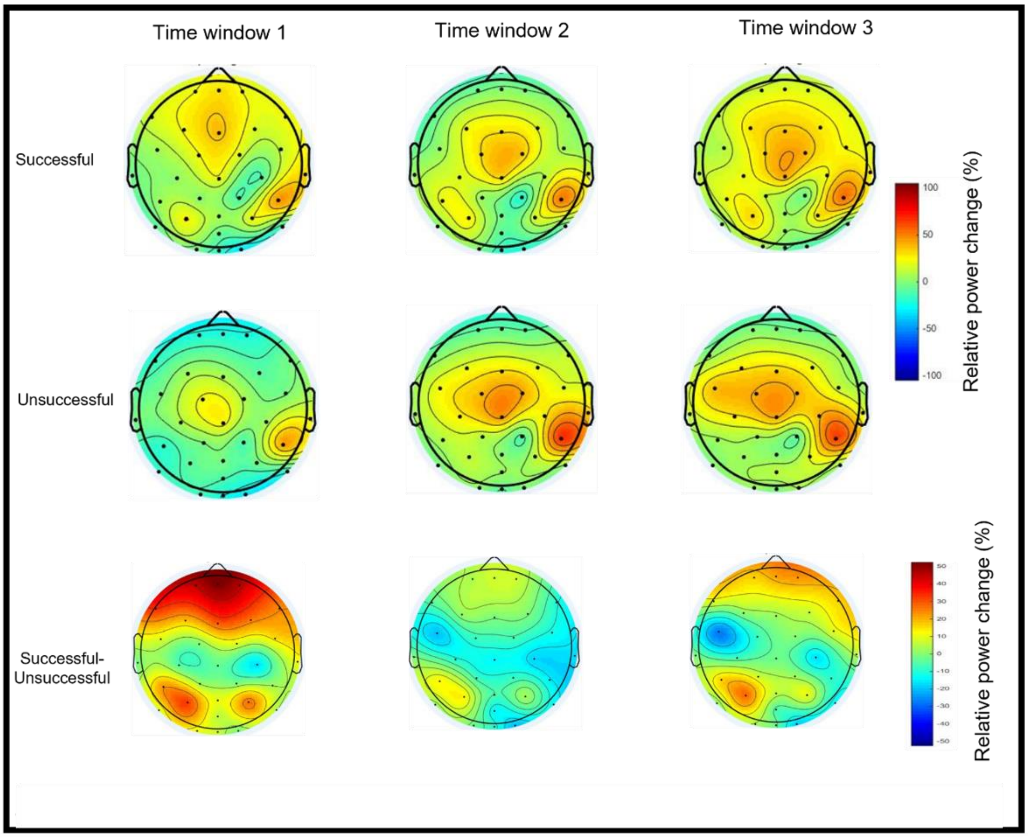


Figure 4.41. The scalp maps represent low alpha activity (9-11 Hz) at the all time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

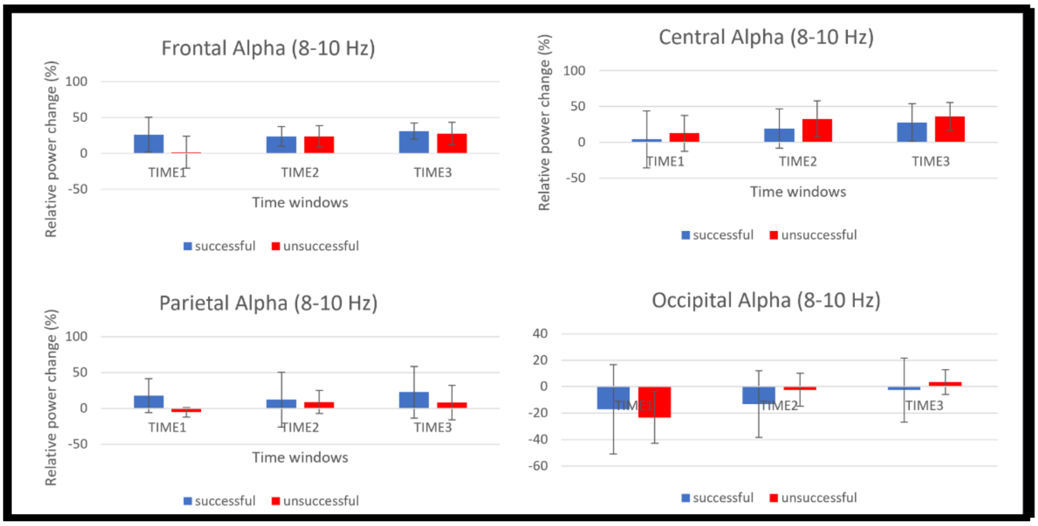


Figure 4.42. The figure exhibits the low alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

4.6.1.5.3 High Alpha (10-12Hz)

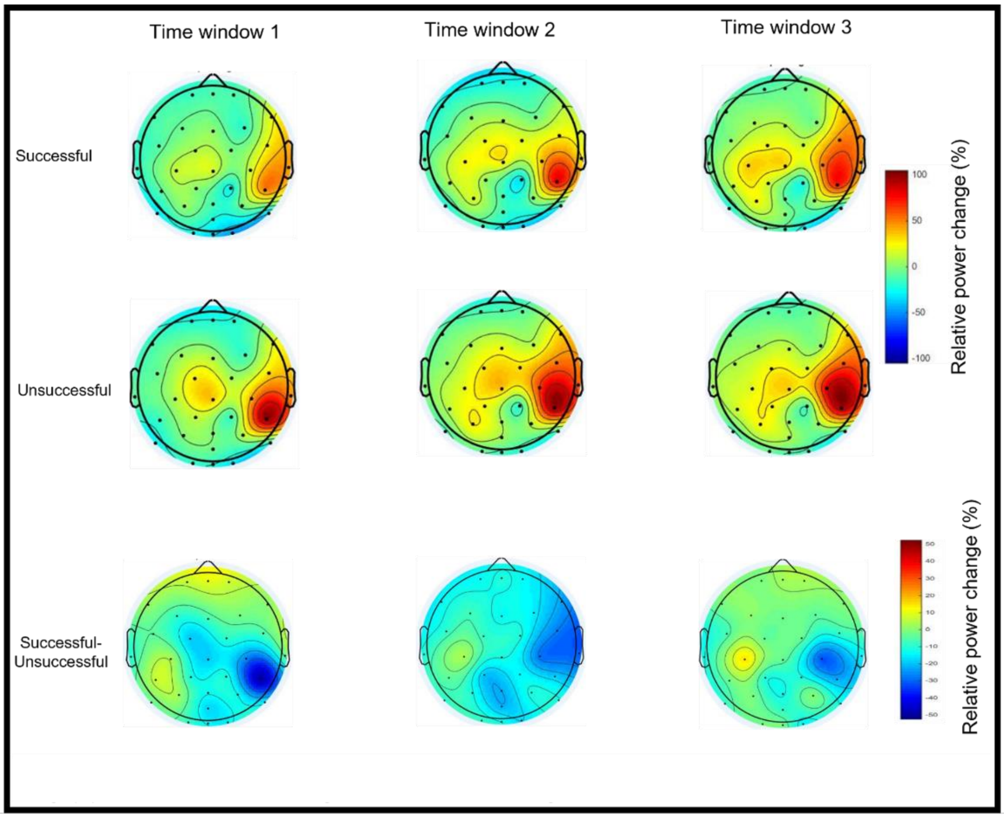


Figure 4.43. The scalp maps represent high alpha activity (11-13 Hz) at all three time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

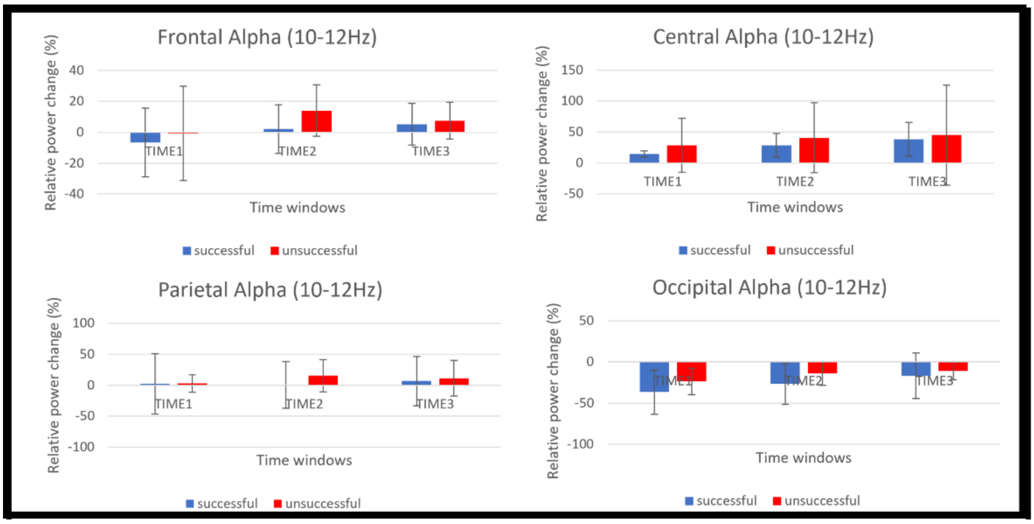


Figure 4.44. The figure exhibits the high alpha mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

Additional Targeted Analysis Alpha Frequency (8-12Hz)

Additional targeted analysis was conducted, focusing on electrodes FC1/Cz/FC2 electrodes. As seen in Figure 4.39, 4.41 and 4.43, there was greater overall alpha power throughout the preparation period of unsuccessful shots compared to successful shots. Interestingly, the observed alpha power pattern was more pronounced in the high alpha sub band (10-12Hz). Figure 4.45 exhibits the mean and confidence intervals for overall alpha (8-12Hz) and low- (8-10Hz) and high- (10-12Hz) alpha sub bands. The pattern of means and confidence intervals suggests, however, that no differences were exhibited across performance levels and time windows within the alpha frequency for Participant 2.

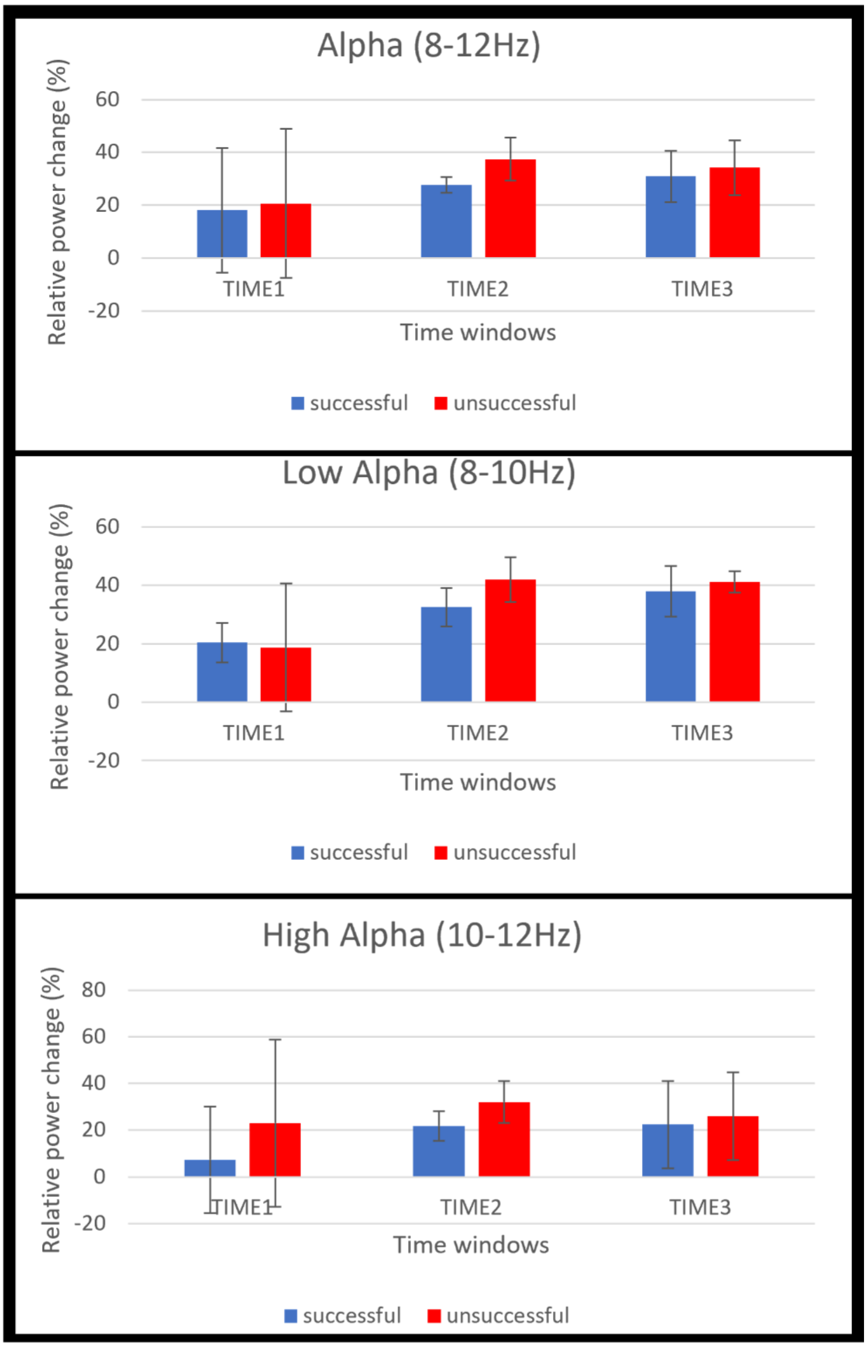


Figure 4.45. The figure exhibits the overall alpha and low- and high-alpha mean power in percentage change for successful and unsuccessful performance across all time windows averaged across C4/CP6 electrodes. The error bars represent the 95% confidence interval of the mean.

4.6.1.5.4 Theta Frequency (4-7Hz)

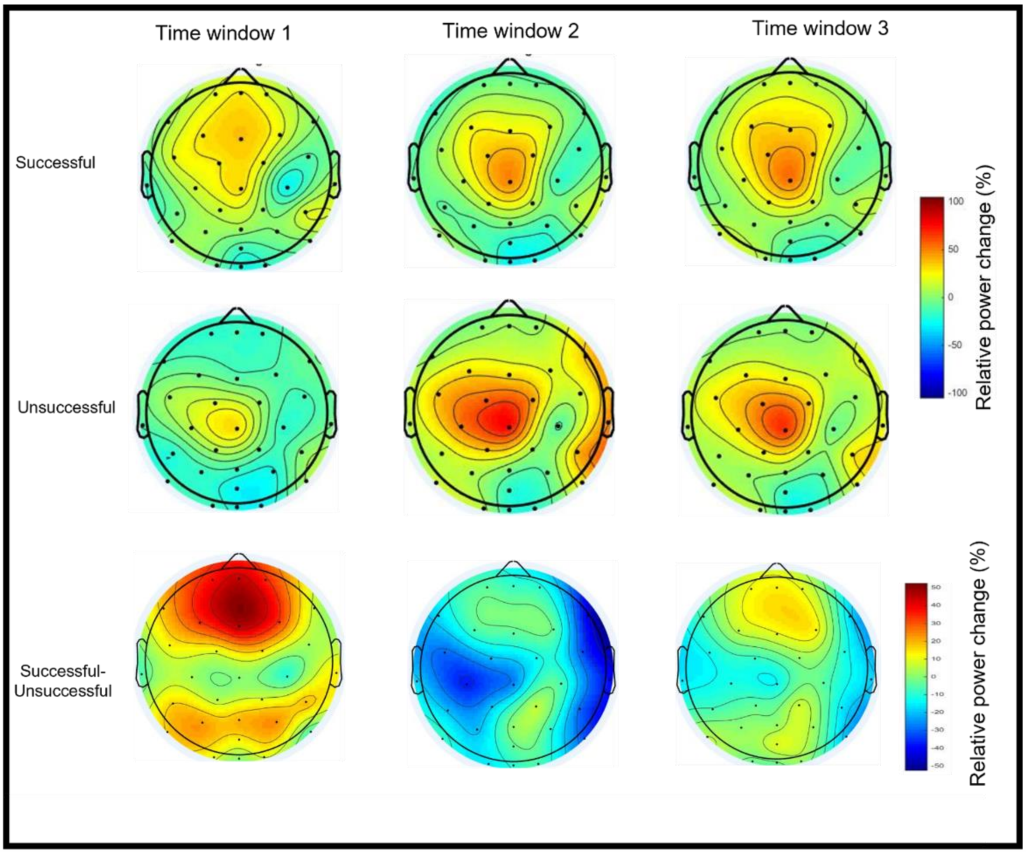


Figure 4.46. The scalp maps represent theta activity (4-7 Hz) at all three time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.46 there is a focal, fronto-central increase of theta power throughout the preparation of period, the amplitude of which becomes progressively larger as the athlete gets closer to pulling the trigger. Interestingly, the amplitude of theta power seems to be larger before successful shots between 3000 to 2000ms and 1000 to 0ms before pulling the trigger compared to unsuccessful shots, but the pattern of the difference is reversed during the 2000 to 1000ms. The difference between the two conditions was quantified by pooling the theta power from electrodes Fz, F3 and F4, in each of the time windows of interest; a significant difference between the two conditions has been found during 3000 to 2000ms prior to the trigger pull with more theta power underlying successful performance (Figure 4.47). As for Participant 1, additional correlational analysis was performed to investigate the relationship between theta (4-7Hz) and performance (Appendix A) which has been identified as significant through the Cis analysis. No significant correlations were identified through the analysis.

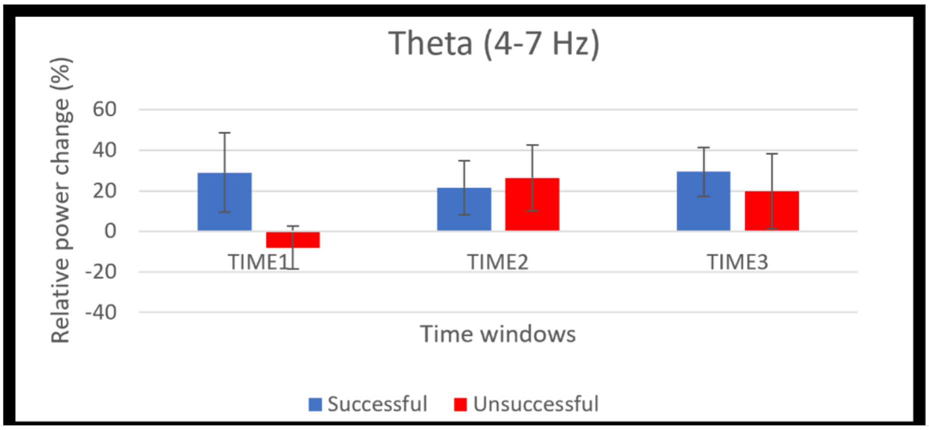


Figure 4.47. The figure exhibits the theta mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal region. The error bars represent the 95% confidence interval of the mean.

Additional Targeted Analysis for Theta (4-7Hz)

As can be seen in Figure 4.46 the pattern of power is maximal over the frontal-central region, thus further examination of theta power over electrodes FC1/FC2/Cz was performed. Figure 4.48 exhibits theta power averaged across electrodes FC1/FC2/Cz, however, no significant difference is exhibited in the mean power underlying successful performance compared to unsuccessful performance.

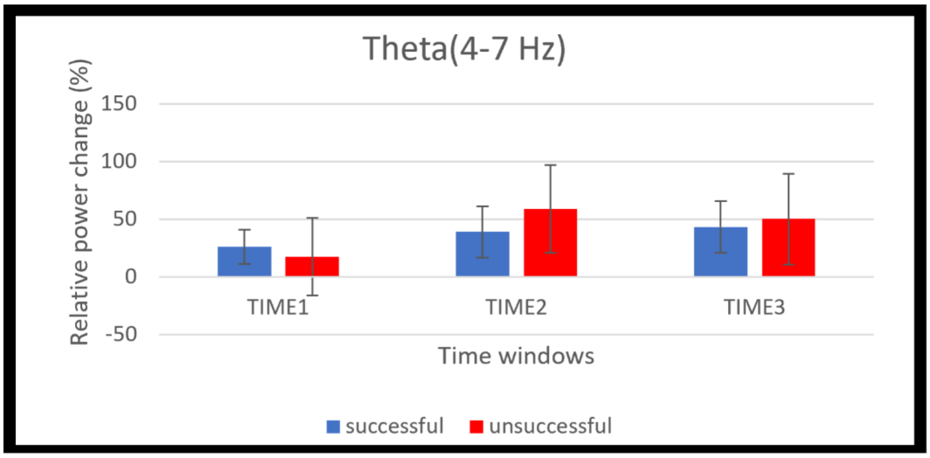


Figure 4.48. The figure exhibits the theta mean activity in percentage change for successful and unsuccessful performance across all time windows at FC1/FC2/Cz. The error bars represent the 95% confidence interval of the mean.

4.6.1.5.5 Beta Frequency (15-30Hz)

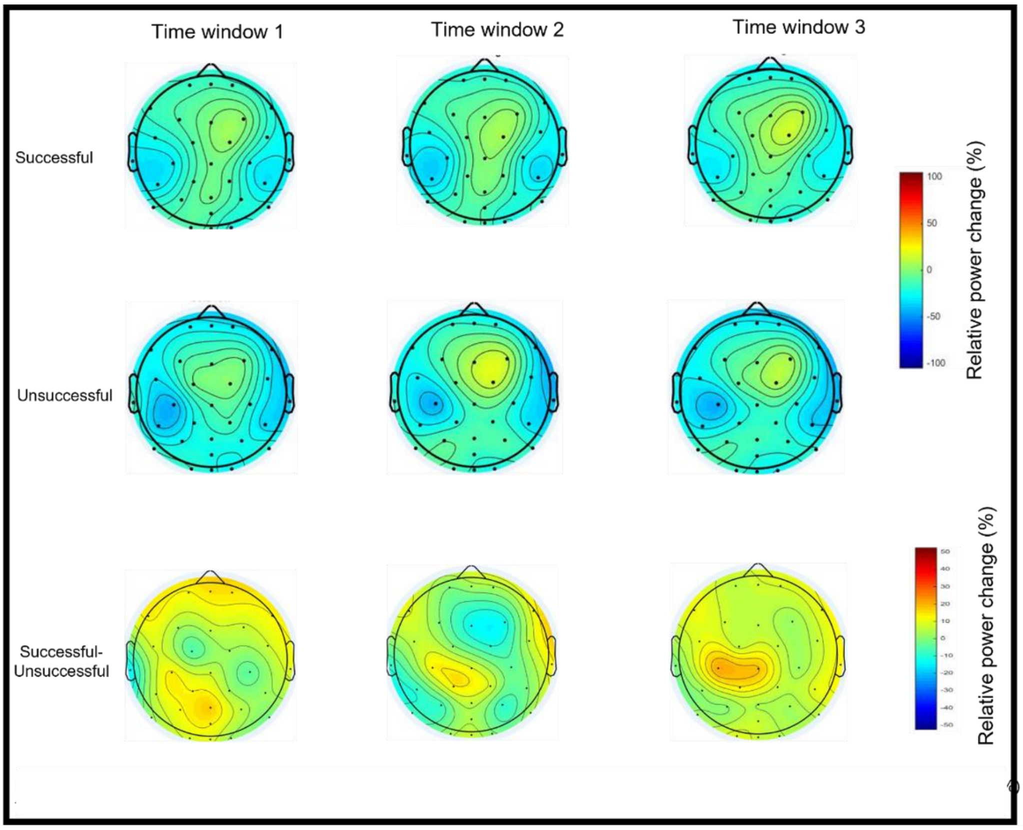


Figure 4.49. The scalp maps represent beta activity (15-30 Hz) at all three time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.49 the topographic maps suggest that there are differences in beta power underlying successful compared to unsuccessful performance. Successful shots are associated with an increase in beta over central electrodes(C3/Cz/C4); the difference between successful and unsuccessful shots appears to be largest during time window 3 (-1000ms to 0ms). However, data analysis did not reveal any significant differences between the two levels of performance (Figure, 4.50).

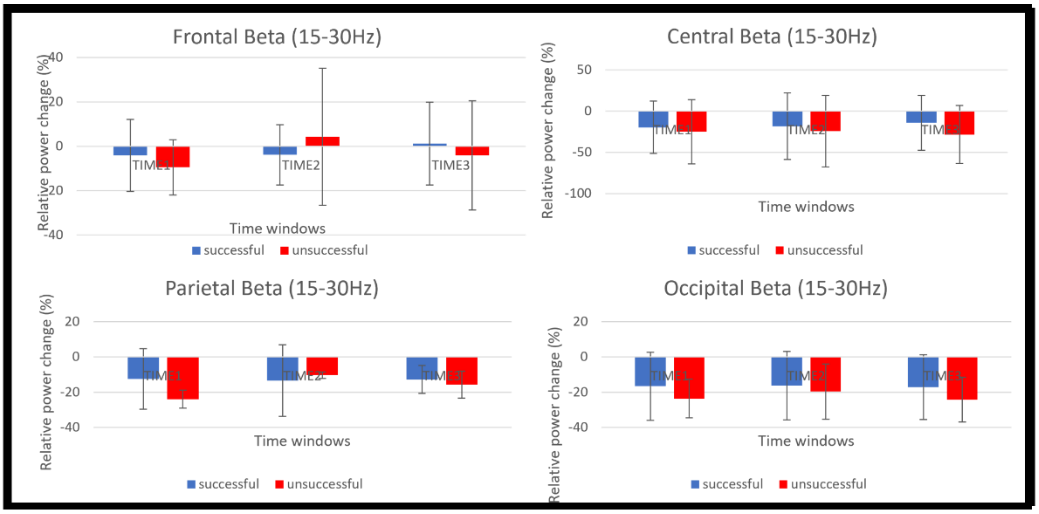


Figure 4.50. The figure exhibits the beta mean activity in percentage change for successful and unsuccessful performance across all time windows at frontal, central, parietal and occipital regions. The error bars represent the 95% confidence interval of the mean.

4.6.1.5.6 SMR Frequency (13-15Hz)

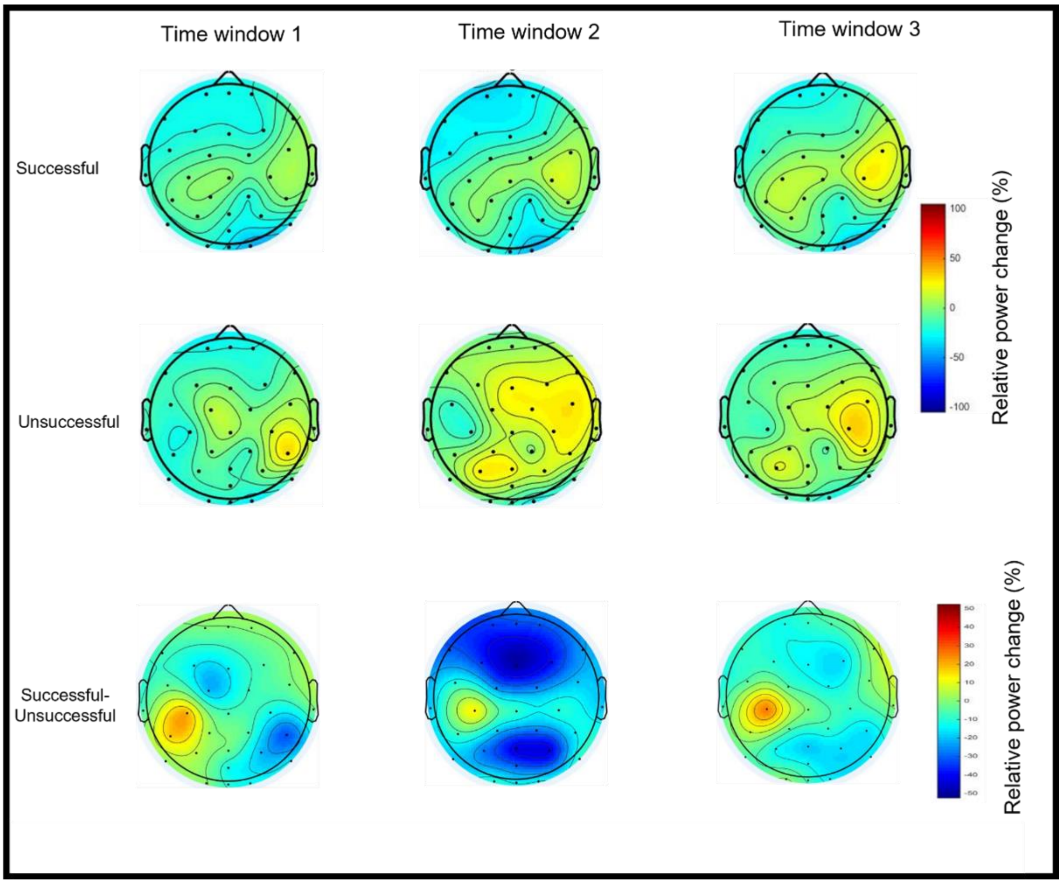


Figure 4.51. The scalp maps represent SMR activity (13-15 Hz) at all three time windows. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 4.51 there seems to be a larger increase of SMR power underlying unsuccessful compared to successful performance, evident in the topographic maps over frontal electrodes during time window 1 (-3000ms to -2000ms), becoming more evident during time window 2 (-2000ms to -1000ms) at frontal and parietal electrodes. According to previous literature SMR power differences are prominent over the central (C3/Cz/C4) region. However, as can be seen in Figure 4.52, there is no reliable difference in SMR power here.

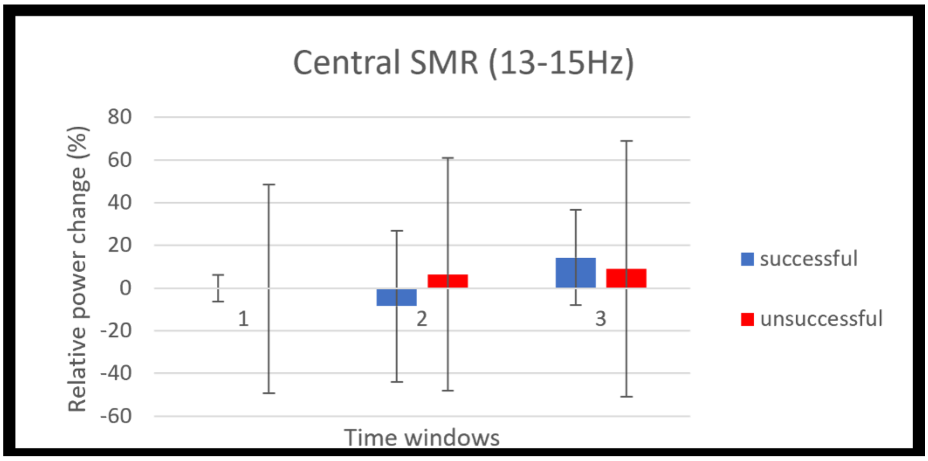


Figure 4.52. The figure exhibits the SMR mean activity in percentage change for successful and unsuccessful performance across all time windows at central region. The error bars represent the 95% confidence interval of the mean.

4.7 Discussion

The current chapter follows the work of Klimesch (1999), examining the effect of assessing individually tailored EEG, using the Individual Alpha Peak Frequency (IAPF) approach. We employed this approach during the exploration of differences in neural activity characterizing successful and unsuccessful performance in two elite Air-Rifle shooters – reflecting the desire to understand the cognitive and neural basis of sporting success at the level of each individual athlete. Our primary aim was, therefore, to explore the EEG profiles of individual shooters, characterising similarities, and differences between the shooters. One key consequence of this approach was the need to adopt an alternative analysis strategy based on the ‘new statistics’ (Cumming, 2014). Whilst visual inspection approaches have been used before in the EEG sports literature, the current investigation is the first to our knowledge to have employed the new statistics to examine individual athletes. Finally, as well as examining variability at a neural level, we also aimed to explore behavioural viability based on individual kinematic data acquired through the SCATT device. In particular, we examined issues around the baseline period employed in the assessment of EEG, asking whether the data suggest the need to employ individually tailored baseline periods.

The first methodological issue raised in the current study was whether the use of IAPF is warranted. Identifying the IAPF for the two shooters within an eyes-closed task revealed that Participant 1 had an alpha frequency range of 9-13 Hz, compared to the *a-priori* frequency range used within the sporting and wider neuroscience literature of 8-12Hz. By contrast, for Participant 2 the IAFP remained in the same *a-priori* frequency range usually investigated in the literature. The consequence of the change in the definition of alpha for Participant 1 is discussed in more detail below. More importantly, however, and regardless of the specific results, the current data demonstrate that the IAPF approach can make a difference to the definition of alpha (and as a result, to the definition of other frequency bands), at least for some individuals. Given that the assessment of the IAPF involves relatively minor additional data collection, and there is no loss of information when the definition of alpha is unaffected, our data strongly suggests that the assessment of the IAPF should be routinely employed in sports. Importantly, however, in the remaining empirical chapter of this thesis (Chapter 5) IAFP was not recorded and calculated for our athletes, because we collected the curling data prior to examining the outcomes from Chapter 4 (based on the schedules and availability of the athletes).

The second methodological issue addressed here was the appropriateness (or viability) or examining individual athletes without recourse to traditional statistical testing. Here we used a combination of visual inspection and the assessment of 95% confidence intervals across successful and unsuccessful shots. Whilst the results of the current study revealed no evidence for reliable differences in the EEG in the majority of frequency bands and time windows, the data did nonetheless reveal robust differences in alpha for Participant 1, and theta for Participant 2, suggesting that individual athlete's EEG can be examined using the new statistics approach. The specific findings are discussed in more detail below; here we highlight that these findings provide some support for the adoption of an N of 1 approach. The findings suggest, however, that substantial amounts of data are required within each athlete if this approach is to be adopted. The original intention was to examine each athlete over enough sessions to be able to examine whether the pattern of effects was consistent over time (i.e., between sessions). Unfortunately, however, the practical constraints associated with collecting data around the athletes' routine practice and competition commitments meant that we were not able to acquire enough data to make such analysis worthwhile. The results presented here were all averaged across multiple recording sessions (involving far more shots than has typically been examined in previous studies), but the data nonetheless revealed a large degree of variability – reflected in large/wide confidence intervals – such that even relatively large differences in EEG power were often nowhere near being statistically different.

The third methodological issue raised in the current study concerns the appropriateness of the baseline period used in the assessment of EEG data. As was highlighted in Chapter 3, within the wider sporting literature a range of different pre-shot periods have been examined (ranging from 3 to 5 seconds before the shot), often without specifying or employing a baseline. Where baseline periods have been employed, they have typically involved a 1000ms window prior to the pre-shot period of interest – typically a baseline of 4-5 seconds. Critically, the assumption behind the use of a baseline period is that this provides a time window when the cognitive processes of interest (i.e., that are engaged during the preparation to shoot) are not yet engaged. To our knowledge the current study represents the first attempt to investigate this issue within the literature.

The data clearly indicates that the shooters were engaged in aiming during the time windows that would typically be used as a baseline. Based on kinematic data provided by the SCATT device we were able to provide clear evidence that there are indeed individual differences in the timing of the shooters' behaviour – our two athletes had quite distinct timing profiles (see Figures 4.2 and 4.3) suggesting that the time taken to aim towards the target varied from shot to shot, from one shooter to another, and within each shooter. The differences identified at an individual level strongly suggest that baseline periods should be individually tailored to each athlete (e.g., informed by kinematic data or equivalent measures such as the initiation of the swing in golf putting). Based on our assessment of the kinematic data, in the current study we employed baseline periods that were more than 10 seconds before the shot, adjusted for each shooter, to ensure that neither shooter was actively engaged during the baseline. Clearly the assessment of EEG using baseline time-windows that do involve active preparation has implications for the neural pattern revealed and for the interpretation of the EEG findings reported. Importantly, the current findings suggest that future studies should carefully examine behaviour in relation to the baseline employed, to establish a baseline that is not contaminated with pre-shot processing. In the next chapter (Chapter 5) we establish a baseline period for curling by examining behaviour and establishing an appropriate baseline period which, to our knowledge, does not contain any pre-shot processing. For the purposes of the curling sport, we send a manual trigger to the EEG data, reflecting when the athletes start initiating the stone delivery phase. We are confident that our baseline selection for the curling task does not involve any active preparation and will not have any implications for the neural patterns which will be discussed.

Having outlined the major methodological outcomes of the current study, we first discuss the behavioural outcomes prior to discussing the specific EEG findings. The present behavioural findings demonstrate that employing an individualistic approach has an impact on the pattern of results reported. For Participant 1 two significant correlations have been reported. A weak positive correlation was found between 10a0 and performance. As has been described in the Section 4.5.3 (Material) 10a0 defines the percentage of the last three seconds of aiming time and where the point of aim is within the 10.0 ring. The result does make sense from an applied perspective for this individual. Participant 1’s average score was 10.2 so by spending more time in the 10.0 ring that would lead to more successful performance. However, this was not the case for Participant 2 as their average score was 10.4 and no significant correlation was exhibited. Moreover, breach was negatively correlated (moderately) with shooting performance for both Participants 1 and 2. According to the description provided in Section 4.5.3 (Material) breach is the measure between the centre of the aim and where the shot lands on the target. So, from an applied perspective the significant correlation for both shooters between breach and score would have been expected. Coaches and athletes place a lot of significance on the breach variable within the SCATT data and based on the pattern of results outlined above, it is important for athletes to minimize the distance between the aim of the target (within the last three seconds). Although the SCATT software has been widely adopted and used within the shooting domain, the variables included in SCATT such as breach do not appear to add very much regarding shooting performance. Put simply it is obvious that the closer the aim is to the target the higher the performance. Nonetheless, coaches and sports practitioners should take into account the average score of each athlete and investigate performance and the relationship with SCATT on an individualistic level as the relationship between shooting performance and SCATT variables differs from individual to individual.

Having outlined the behavioural outcomes of the current study, we now focus on the specific EEG findings. In Chapter 3 (Section: 3.2.1 Alpha Frequency) we outlined the inconsistencies and limitations arising within the sporting literature in relation to the alpha frequency. In line with the work provided by Klimesch (1999), the present findings suggest that the failure to account for variability in the IAPF could explain many of those limitations. Most EEG studies examining frequency data define alpha rhythms in a fixed narrow band of (8-12Hz), and this is the case in the sporting literature. The present findings demonstrate that employing an IAPF approach can significantly influence the pattern of effects reported. For Participant 1 a relative change in *a-priori* alpha power (8-12Hz) was found for successful performance in comparison to unsuccessful performance across fronto-central electrodes. More specifically, during the first-time window (-3000ms to -2000ms) low alpha power (8-10Hz) was greater for unsuccessful than successful shots, whereas for high-alpha (10-12Hz) there was greater power for successful than unsuccessful shots. In contrast with this result, when shooting performance was investigated with an IAPF a somewhat different pattern emerged. Analysis once again revealed a change in alpha power for successful compared to unsuccessful shots over fronto-central electrodes, but the difference was restricted to an increase in high alpha (11-13Hz) for successful compared to unsuccessful shots. In addition, the difference in alpha revealed using IAPF was longer lasting, showing clear differences in both the first- and second-time windows (from -3 to -1 second before the shot).

Put simply, the pattern of results reported here suggests that tailoring the analysis of EEG data matters for the interpretation and explanation of results – at least for studies that try to account for performance differences in terms of alpha power (Haegens et al., 2014). The present findings provide strong support for the claim that calculating the individual alpha peak frequency will provide a more accurate estimation of the alpha power within and between individuals (Doppelmayr et al., 1998). Previous studies have also suggested that using an IAPF estimation will provide a more accurate estimation of neighbouring frequencies, as portions of alpha power might fall outside the a-priori (8-12Hz) range, and power from neighbouring frequencies (theta, beta) might be included in the a-priori definition of alpha power (Haegens et al., 2014). Here, however, we examined theta within successful and unsuccessful performance using an a-priori (4-7Hz) band and a more targeted IAPF-based theta (5-8Hz) band. However, the observed pattern of power for theta was similar to the one observed using the a-priori band of 4-7Hz, and in this individual at least, no differences were observed in either analysis.

As noted above, the different pattern of activity found across the *a-priori* and individual alpha peak frequency clearly has implications for our understanding of the role of the alpha band across successful and unsuccessful performance. In particular, different cognitive processes have been associated with low- and high- alpha power. Research suggests that low-alpha power reflects the subject’s global attentive readiness and effort, whereas high-alpha power has been suggested to reflect ‘more task-related processes (Del Percio et al.,2009). Whilst a traditional *a-priori* alpha analysis suggested that there were changes in both low- and high- alpha, the IAPF results confirmed that the difference was only reliable for high alpha. From a functional perspective, therefore, the current findings suggest that for Participant 1 successful performance was associated with an inhibition in task-related processes. A possible interpretation of selecting and inhibiting task related processes can be readily explained in relation to the neural efficiency hypothesis. The neural efficiency hypothesis suggests that cortical activity is reduced in expert athletes after prolonged periods of training. Studies have shown expert athletes require less cortical activation when performing motor tasks compared to novices (Del Percio et al., 2009a). Previous researchers have asserted that elite athletes are easily able to engage cortical processes once they have been learned over a series of training sessions (Del Percio et al., 2009). It has been suggested that trained motor tasks are performed by athletes by suppressing unnecessary processes and performing the required processes automatically (Kerick, Douglass & Hatfield, 2004).

A potentially important aspect of the current findings is the fact that the change in alpha was sustained from -3000ms to -1000ms prior to the trigger pull, suggesting an extended period of inhibition is critical for successful shots (at least in this individual). Moreover, it is notable that the significant difference in alpha was not present in the final second before the shot, however the same pattern of activity was observed (i.e., more alpha underlying successful performance in the last second). The fronto-central increase in higher alpha power might be explained by inhibiting processes during the preparatory period of aiming over the premotor and motor region. Given that more alpha power is associated with inhibition processes, the changes in alpha power seen here suggest that successful performance is achieved when the shooter inhibits processes that have been learned over time and do not require effortful processing. From an applied perspective this raises the possibility that for this particular expert shooter, it might be beneficial to not overthink the motor processes involved within the shooting task such as the trigger pull, and hand stabilization used for stabilizing the Air-Rifle (Hummel et al., 2002).

In contrast to the increase in alpha observed for Participant 1, for Participant 2 no differences were found within alpha. For Participant 2 successful performance was associated with an increase in theta power over frontal electrodes from -3000ms to -2000ms. Increases in theta power within the frontal midline region (Fz) have been reported in previous studies across golf and rifle shooting sports (e.g., see Baumeister et al., 2008; Doppelmayr et al., 2008). From a functional perspective, increases in theta power have been reported as a characteristic of expert performance, reflecting sustained attention and concentration (Lagopoulos et al., 2009) during the preparatory period leading up to the shot in experts compared to novices. Consistent with this view, increases of theta power characterizing successful performance for Participant 2 would suggest that the Air-Rifle shooter is maintaining effortful sustained attention and concentration. Sauseng et al., (2007) reported the importance of sustained attention and how it related to frontal midline theta. In their study, participants had learned and performed complex finger movements and frontal midline had increased alongside increasing task demands. The authors suggested that frontal midline theta is associated with attention which supports the allocation of cognitive resources. However, Doppelmayr et al., (2008) suggested that whether the functional importance of frontal midline theta is in allocating attention or is related to the expert's decision of when to pull the trigger based on volitional decision (anterior cingulate areas related to top-down processes, cf. Buschman and Miller, 2007) remains unanswered. In our previous study (Chapter 3), we suggested that lower theta power was associated with successful performance, but that excessive amounts of attentional engagement and effortful processing might be detrimental to performance. There is, however, evidence suggesting that expert athletes possess the ability to consciously monitor the mechanisms relevant to the task, adaptively focusing their attention on the most important aspects of the task at the current time (cf. di Fronso et al., 2018). From this perspective the data suggest that our Air-Rifle shooter (Participant 2), possesses the ability (due to experience and expertise) to focus and allocate successfully cognitive resources required for the successful execution of the task.

More broadly, an integrated view of the findings within this study leads to the suggestion that the different EEG profiles reflect the fact that different mechanisms are activated and engaged in each individual athlete. Put simply, the data are consistent with the idea that Participant 1 inhibits motor processes by automatically performing the motor actions of the trigger pull (finger movement/right index finger) and controlling the stability of the Air-Rifle. In contrast, Participant 2 exhibits a quite different profile and achieves successful performance in a different way, by maintaining just the right amount of attention at the right time, by monitoring the information relevant to the task and focusing on the information required to successfully perform the task and deciding when to pull the trigger (as per previous accounts of the functional significance of theta in volitional decision, see Buschman & Miller, 2007). From a cognitive neuroscience perspective this finding is important because it helps to explain why such different results have been found across sports EEG studies. More importantly, perhaps, from an applied sports perspective this finding reinforces the view that studies of elite sporting behaviour must take into account individual variability if they are to fully explain why (and how) specific individuals achieve elite status and others do not.

To our knowledge the current study is the first to explore differences between *a-priori* and IAPF measures of alpha power. Taken together, the findings from Participants 1 and 2 highlight the importance of calculating IAPFs. Although the IAPF approach made no difference to the findings for Participant 2, for Participant 1 the pattern of effects differed across high- and low- alpha bands, and over time, suggesting that the traditional approach could lead to a substantial misinterpretation of the results. One area of research where changes of this nature are likely to be of particular importance is neurofeedback. As noted in Chapter 1 neurofeedback is of considerable interest within sports because it offers the possibility of enhancing performance based on the measurement of an individual's neural processing. As Hammond (2007) notes, however, the current approach to developing neurofeedback tools is based on standardised measures, and no account is taken of individual differences, or the different task demands across various sports. Our results support Hammond’s suggestion that a more tailored, individual approach is required if neurofeedback is to become effective.

Finally, our results provide empirical evidence to support the claim that sports practitioners, coaches, and researchers must account for individual differences if they are to provide a complete account of the cognitive and neural processes supporting successful sports performance. In particular, the current findings suggest that the ‘’simplistic’’ one-size-fits-all approach that has been adopted within the sporting domain cannot account for the variability that exists across individuals, let alone across different tasks and sports. Consistent with this view, Arns et al., (2008) have suggested the use of a personalized approach, focusing in particular on the need for task-related ecologically valid training (in real world settings) in the context of each sport. In line with Arns et al., (2008) our next chapter will focus on investigating the neural activity characterizing successful and unsuccessful performance in a curling task. Whilst curling is a closed target sport (like shooting) the demands of curling differ somewhat from other target sports (discussed in more detail in Chapter 5). Given the distinct strategic demands associated with curling it seems reasonable to expect differential mechanisms might characterize performance to those seen in shooting, reflecting the differences in task complexity. In sum, the current study provides a unique examination of individual EEG and behavioural profiles characterizing successful and unsuccessful performance. The present approach represents a significant advance on previous studies in the literature, providing a solid basis for future research to build upon, by examining individual sporting performance with a larger cohort of athletes. Additionally, future studies should investigate individual EEG profiles, and by examining changes in activity from session to session, as underlying performance levels vary within each individual. Future studies should examine the consistency of the individual differences and assess any similarities or differences that might arise from session to session. The current study has provided the basis for such future analysis, as well as making it clear that more trials will be required for a session-by-session evaluation to provide more confidence in any significant differences that might arise.

Chapter 5: Investigating neural activity in a real-world curling task

5.1 General Introduction

Curling is a sport that was invented in Scotland in the 16th century and is often referred to as ‘’chess on ice’’ (Haggerty, 2013). Curling is highly strategic in nature and the basic objective of curling is to deliver a 20kg granite stone to a target at the end of a 150 feet sheet of ice. According to Arns *et al.,* (2008) there is a need in the sporting domain to examine personalized approaches in real world sport settings within the context of different sports. The advances associated with understanding each sport individually will have an impact on professionals and athletes, as any identification of differences in underlying neural activity as a function of performance will be an important step towards interpreting and explaining performance differences across various sports, providing the possibility of adopting EEG profiles characteristic to each sport.

In order to examine differences across sports at a neuronal level, the current chapter focuses on examining EEG data during curling within a group of expert athletes. More specifically, we examine seven expert curling athletes, exploring whether there are specific patterns of neural power associated with different levels of performance within the curling sport. A number of factors motivated the choice of sport. Firstly, to our knowledge, no other studies have been performed on the game of curling whilst most of the sporting literature has focused on sports such as shooting, golf, archery. Secondly, the procedural routine associated with delivering the stone to a target at the end of a 150 feet sheet of ice involves a fixed series of steps, from pushing out of the hack to sliding down the ice and releasing the stone. The procedural nature of curling provides a clear and consistent time-locking point (i.e., the release of the stone), allowing neural activity to be examined in the preparatory period leading up to the release of the stone. Thirdly, curling involves a relatively limited range of movement (the curler must deliver the stone to the target and must maintain postural stability whilst sliding down the ice), which is favourable for the recording of EEG data as the likelihood of muscular artifacts will be lower than in sports that require whole body movements. Taken together, these three factors make curling an excellent test case for exploring the potential markers underlying successful and unsuccessful performance during real sporting behaviour.

The following section will introduce the general and basic context of curling, followed by a review of behavioural studies investigating the elements important within a curling task, prior to describing the methods that were required for this study. There will be no introduction to studies examining EEG specific to curling, as to our knowledge no other studies have attempted to explore the neuronal pattern underlying successful and unsuccessful performance in a curling task.

5.2 Introduction to Curling

Curling is a sport played by teams of four on a sheet of ice that is 150 feet in length and 16.4 feet in width (Clement, 2012). At each end of the ice sheet there are four concentric circles with diameters of 12, 8, 4, and 1 foot, collectively known as the house (Clement, 2012). All team members contribute to the delivery of the stone (two stones for each member). Once all stones have been delivered, the team with the stone delivered closest to the centre (known as the button) of the house earns a point (a point is earned for every rock that is in the house and closer to the centre compared to their opponent’s closer stone). If no stone is in the house, then both teams score zero. Figure 5.1 shows an example of two curling teams playing a game of curling. The image on the left shows an example of a team with the light-coloured stone earning one point and on the right a team with the dark coloured stones earning two points.

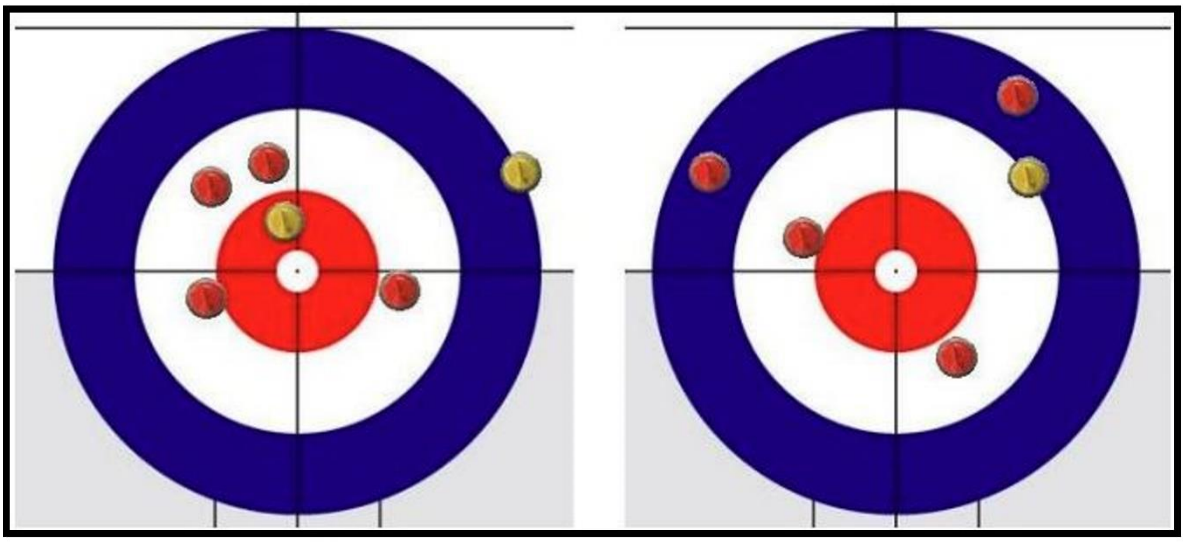


Figure 5.1. On the left of the figure on the team with the light coloured stones are shown which has resulted in the team earning one point. On the right of the figure the team with the dark coloured stones are shown, which has resulted in the team scoring two point.

Note. Adapted from Clement, D. (2012). An analysis of Curling Strategy, pp.1, Copyright 2012 by American Statistical Association.

According to Clement (2012), the comparison of curling to chess originates due to the strategic nature of curling. The strategy within curling concerns exactly where to place the stone and it can be a complex problem for the athletes to solve. As the curling stone is travelling to the house, the sweepers (two team members who did not throw the stone) will, if it is needed, sweep their brooms in front of the stone. Sweeping will increase the ice temperature, reducing the friction between the stone and the ice (Buckingham *et al.,* 2006). Based on the direction the stone is rotating and the side of the stone the sweeper is sweeping, it will allow the stone to stay straight or to curl more whilst travelling to the target (Bradley, 2009). Although the stone dynamics and sweeping strategy within a curling task are unique within target sports, this aspect of curling lies beyond the scope of this thesis.

According to Shank (2012), the delivery of the 20kg polished granite stone to a target at the end of a 150 feet sheet of ice is the basic objective of curling, meaning that accurate control of the stone is the primary motor skill found in the sport of curling. The delivery of the stone is characterized as a coordinated movement requiring precision and stability. It is performed by sliding the stone in a backwards manner, and then swinging it forward on the sheet of ice, whilst pushing out of the hack with the athlete’s dominant leg. Once the athlete has pushed themselves out of the hack they slide down the sheet of ice along with the stone. During this period the athlete is receiving information on the stone’s speed, weight, and the trajectory the stone will follow towards the target (Shank, 2012). Once the player has released the stone, it will follow a curved (curled) path to reach the house, depending on factors such as the speed, the friction between the stone and the ice and the direction provided by the player (given via the handle found on top of the curling stone).

The delivery process is one of the most important skills in the sport of curling (Kivi & Auld, 2012). The main objective of the delivery process is to push out the hack, slide down the ice and release the stone, which will eventually stop at a specific position at the opposite end of the ice sheet (Kivi & Auld, 2012). According to previous literature, a successful stone delivery involves a low, extended lunge position close to the sheet of ice, resulting in a better visualization of the target (Pojskic *et al.,* 2019). Behm (2007), stated that to efficiently execute a successful stone delivery, good balance, stability, and flexibility are considered important qualities in the game of curling. These qualities provide the curler with a stable delivery position, which will lead to better speed and control of the stone (Shank & Lajoie, 2013). Good balance from the curler results in a straight slide, which is vital for a successful shot because it leads to a straight-line delivery, allowing the curler to maintain optimal speed and aim (Shank *et al.,* 2012). Studies in the motor control domain also argue that attention plays a significant role in postural control (Shank *et al.,* 2012). These studies suggest that postural control is attentionally demanding and not performed automatically, whilst supporting the idea that the more complex a task becomes the more attentional demands are required for better postural control (Shank *et al.,* 2012).

In addition to postural stability being central to accurate delivery of the curling stone, effective navigation through the dynamic environment (sliding down the ice) and integrating external information are also crucial for successful performance (Shank *et al.,* 2012). The visual information (sensory input) collected by the athlete during the delivery process within the curling task is critical to developing successful movement leading to a successful shot. The curling task will therefore require an increase in attentional processing, especially closer to the release of the curling stone, as the athletes are not only approaching the target but need to start controlling their body for deceleration on the ice (Shank *et al.,* 2012).

Although the literature has established that the stone delivery process is an essential factor for a successful curling shot, no studies have examined the neural pattern dissociating successful and unsuccessful performance during the delivery phase of the stone. The curling delivery process is a complex and challenging task. Postural control has been shown to require an integration of visual, vestibular, and proprioceptive cues (Maurer *et al.,* 2000). For the purposes of this study, we did not control and measure the balance of the athletes, thus our measure of good posture control will be reflected by successful stone delivery. Theta (4-7Hz) and alpha (8-12Hz) power have been the frequency bands that have been reported as being involved in balance control (Adkin *et al.,* 2006).

In the wider neuroscience domain, studies investigating cortical activity during continuous balance tasks have reported an increase of theta (4-7Hz) power with increasing balance demands in frontal areas (Sipp *et al.,* 2013; Slobounov *et al.,* 2013). Specifically, research investigating cortical activity in balance control tasks have reported an important role for the fronto-central region, including the anterior cingulate cortex (ACC) (Hulsdunker *et al.,* 2015). According to previous research the ACC is believed to be involved in action monitoring and error detection (Veen & Carter, 2002) and outcome evaluation (Jahn, Nee, Alexander & Brown, 2014). Studies examining balance control have reported increases in theta power over fronto-central regions and/or over the ACC which have been associated with better task performance and have been suggested to reflect identification of balance instability and correction (Anguera, Seidler & Gehring, 2009). However, during trials in which balance was unstable there was no significant difference in theta power over fronto-central and ACC activity, which confirms the crucial role of theta power at fronto-central and/or ACC in detecting unstable posture (Slobounov et al., 2006).

The functional significance of the frontal areas and their crucial role in balance control has also been supported through longitudinal studies that have examined the effects of balance training on neuronal structure (Sehm *et al.,* 2014). It has been reported that the volume of gray matter increased in the frontal regions after a six-week continuous balance control training and was positively correlated with improvements in balance performance (Taubert et al., 2010).

In addition to theta (4-7Hz) power being involved in balance control, alpha (8-12 Hz) power has been found during continuous balance tasks and has been indicative of the attentional demands required for balance control. Increases in alpha power have been suggested to inhibit task-irrelevant brain regions, whereas alpha reductions reflect an increase in information processing (Del Percio *et al.,* 2007). Similarly, Edwards *et al.,* (2018) examined the electroencephalographic correlates of continuous postural tasks of increasing difficulty and reported that central and parietal regions were actively involved in the continuous balance control. The researchers reported a reduction in low (8-10 Hz) and high (10-12 Hz) alpha power with increasing task difficulty within the central and parietal regions. Based on these findings Edwards and colleagues suggested that the bilateral reductions of alpha power at central and parietal regions reflect the involvement of those areas during a balance control task (Edwards *et al.,* 2018). It has been suggested that reductions in alpha power seen over parietal regions might be suggestive of increases in external sensory attention and information processing (Edwards *et al.,* 2018). Additionally, the alpha power reduction exhibited within the central region might be suggestive of increased motor processing that is required for the specificities of the balance task (Edwards *et al.,* 2018).

The sensorimotor rhythm (SMR) (13-15Hz) has been suggested to reflect the preparation, execution and imagery associated with a motor action and has been previously recorded over the sensorimotor cortex (C3 & C4 electrodes). The sporting literature (Cheng *et al.,* 2017) and our findings from Chapter 3 (3.8.2.4 SMR time frequency analysis) suggest a link between SMR and better programming and planning of a movement. Additionally, beta (15-30Hz) activity has been reported as occupying an important role in motor control and movement preparation and changes within the beta frequency have been reported in previous sporting literature (Del Percio *et al.,* 2009*)* and in our findings in Chapter 3 (3.8.2.3 Beta time frequency analysis).

As has been discussed in the introductory chapter of this thesis (Chapter 1: Introduction) there is a need for studies within the sporting domain to examine a wider range of frequencies in addition to the alpha frequency and assess whether SMR and beta activity can explain any differences in movement preparation and planning that underlies successful performance. From this perspective and as this is the first study investigating EEG changes in a curling task, SMR and beta activity will be examined in relation to curling performance.

Circular data Analysis

Circular data arises in many fields of research, especially where the data are investigated regarding movement and direction (Rivest *et al.,* 2015). Within the social sciences circular data has arisen in the field of cognitive and experimental psychology (Cremers, Mainhard & Klugkist, 2018). For example, studies investigating cognition underlying human sense of direction will ask a participant during study to point north, or to walk to a target object. The closer the participant is at pointing, or walking, towards the designated direction the better sense of direction they are judged to have (Cremers, Mainhard & Klugkist, 2018). As well as indicating how accurate the participant is, circular data can also be used to characterise how consistent behaviour is (e.g., identifying bias or variability). Although circular data is collected in specific areas of cognitive and experimental psychology, the knowledge and understanding of such data is relatively poor in the wider research domain (Cremers, Mainhard & Klugkist, 2018). One barrier to the use and understanding of circular data is that it behaves quite differently from linear data. For example, circular data can be represented on circles, at which measurements of 0° and 360° would represent the same direction, whereas on a linear scale 0 and 360 would be located at opposite ends of a scale (Cremers, Mainhard & Klugkist, 2018).

For the purposes of this study circular descriptive statistics will be exhibited in the results section to capture variability in curling performance. Circular statistics calculate the resultant vector, mean resultant vector length, R and variance. The spread of the stones is reflected through the R value and circular variance. If the spread of stones is concentrated at a single value (homogeneity) the resultant vector will have a length close to 1 and small variance. If the stone locations are spread out the resultant vector will have a length close to 0 and larger variance. Put simply, the more concentrated the stones are around the mean direction (button), the lesser the circular spread of the data (resultant length closer to 1) and smaller variance. Additionally, the data will be presented graphically for visualization purposes and better understanding. To our knowledge, this is the first study to investigate behavioural performance within a curling context using circular statistics. We believe that the use of circular statistics will provide further information on the stone variability and pattern of behaviour of our athletes. We strongly believe that the use of circular statistics will benefit coaches and sports practitioners in further investigating behavioural profiles of curling athletes.

The current study aims to examine the neural correlates associated with successful and unsuccessful performance in a group of elite curler athletes. This is the first study, exploring the neural patterns underlying successful sporting performance in elite curler athletes. Curling is a target-based sport, and it will therefore be particularly interesting to examine whether the neural mechanisms found in previous target sports (golf, shooting) apply within the context of curling. To address this hypothesis the study employed seven elite curlers and collected as many trials as possible (for EEG processing and analysis). EEG data acquisition was conducted over 8 blocks consisting of 8 stones for each athlete, resulting in 64 stones in total for each athlete.

The following sections will outline the methods, procedure and processing analysis for this chapter, followed by the results section which will examine the neural power characterizing the successful and unsuccessful performance by examining performance within the alpha, theta, beta and Sensori-motor rhythm frequency range. For the purposes of this study, the athletes were required to deliver the 20kg granite stone inside the 4 feet circle. As in previous studies the data collection in the current study was developed in association with the curling coaches and athletes. As a result, performance was only considered to be successful if the stone landed in the 4-foot area. A total of seven athletes performed the curling procedure (no other player was on the ice with them) which consisted of 8 blocks of 8 stones each, resulting in each player delivering a total of 64 stones. To our knowledge, no existing studies have explored the neural correlates associated with the game of curling.

5.3 Methods

5.3.1 Participants

The study employed seven participants (N=7; male=6), experts in curling. Participants were recruited through SportScotland and were elite athletes engaged in International-level curling competitions at the time of recording. All participants were right-handed, right eye dominant and had normal or corrected eye vision. The participants' ages ranged from 19 to 25 (mean age was 22.3 years). The experiment was reviewed by the ethics committee (GUEP) of the University of Stirling. The athletes took part in the research voluntarily, understood the experimental process and purpose, and provided written informed consent to participate.

5.3.2 Experimental design

The curling arena was located in Stirling. The study design was intended to provide as many trials as possible for each athlete, consequently for each athlete EEG data was recorded over a series of 8 blocks, each consisting of 8 stones. In total, therefore, the curling task consisted of the curlers delivering 64 stones whilst sliding down the ice and aiming for the 4-feet circle (cf. Figure 5.2). EEG was recorded continuously throughout the study, with time locking triggers generated through two manual button press triggers on each shot, first when the athlete pushed out of the hack and second when the stone was released. The triggering of the athlete pushing out of the hack served as an indication of when the stone delivery process would emerge, providing information regarding the selection of an appropriate baseline period prior to action initiation. The timestamping of the stone release was crucial because this study aims to examine neural activity during the period leading up to the stone release.

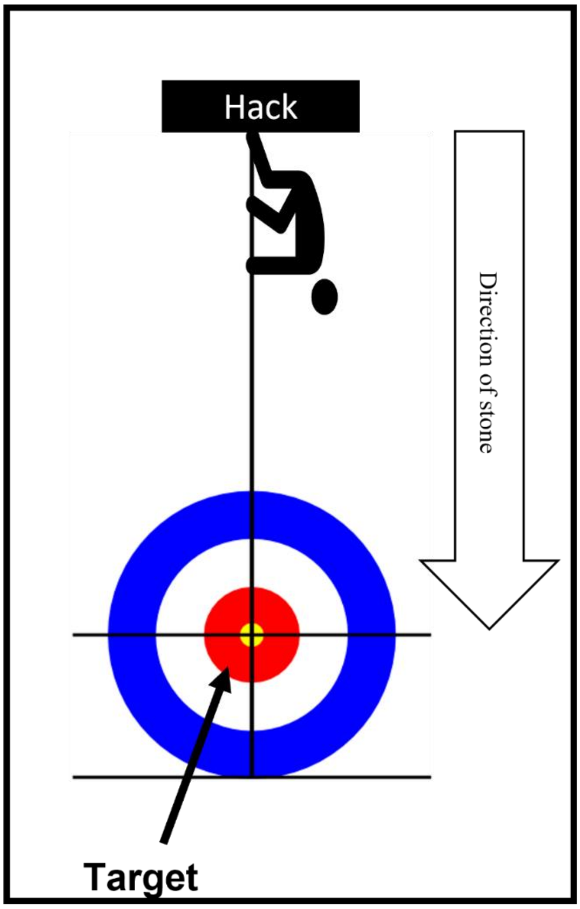


Figure 5.2. The figure represents the target area (4-foot) for the purposes of the curling task used for within this study. The athlete pushes out of the hack and slides down the ice with the stone. The stone is considered successful/hit if it lands within the 4 foot area, reflected as the red and yellow circles in the diagram.

5.3.3 Material

EEG data was recorded via 32 Ag/AgCl electrodes located in an elasticated headcap and connected to a battery powered portable amplifier (ANT-NEURO, Enschede, The Netherlands). The digitization rate of the system was set at a sampling rate of 500 Hz, and data were prefiltered with a high pass filter of 0.0016 Hz and low pass filter of 250Hz. The electrodes were positioned according to the International 10-20 system (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2). Electrode AFz served as the ground electrode and CPz as a common reference. Electrode impedance was measured prior to each recording session and each channel was maintained below 10 kΩ. The timestamping of the events was achieved through a manual button press, which marked the release of the stone.

5.3.4 Procedure

Prior to the experiment, the participants were given general information regarding the functional and practical aspects of the EEG technique in both verbal and written formats. Moreover, the participants were informed that the experiment was conducted in accordance with the guidelines of the University of Stirling Research Ethics Committee (GUEP), that their data would be stored and treated anonymously, and that they had the right to end their participation in the study at any time without any consequences. Participants were then invited to provide their written consent to confirm their voluntary intention of taking part in the study.

During the capping procedure, which lasted approximately 45 mins, participants were seated on a chair in a room within the curling range. Measurements of the participants' heads were used to set up the scalp location sensors based on the International 10-20 system (Jasper, 1958). The gap between each electrode and the scalp was filled with conductive gel, and the experimenter used a disposable blunt needle to increase the sensor conductivity. The electrode impedance was kept below 10 kΩ for each channel.

Following capping, participants were asked to undertake a short training session to warm up, which consisted of approximately 5 stone deliveries towards the house. The participants would let the experimenter know when they felt ready to start the experiment. Participants were instructed to follow their normal training routine and if required to take breaks between every 8 stones. Once data collection was complete the electrode cap was removed, and participants were debriefed. The EEG data was then exported using the built-in data acquisition software (ASA, ANT-neuro). Continuous data was then stored on an encrypted hard drive, before proceeding with further processing.

5.3.5 Data Processing

EEG data were analysed using the EEGLAB open-source toolbox (Delorme & Makeig, 2004) and custom MATLAB scripts (version 2014, The Mathworks Inc.). At the preprocessing stages the continuous data were visually examined and segments that displayed high levels of noise (e.g., caused by channel disconnections) were manually rejected. Following the removal of noisy data, each dataset was then filtered with a low pass filter of 40 Hz and a high pass filter of 1 Hz. Next, Independent Component Analysis (ICA, Bell & Sejnowski, 1995) was performed on each dataset, identifying a set of Independent Components (ICs) (e.g., a total of 30 components for each dataset) for consideration as artifacts. The ICs were assessed using SASICA (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact Correction, Chaumon, Bishop & Busch, 2014) to identify artifactual ICs for rejection. Although SASICA allows manual rejection of components (e.g., based on visual inspection) to ensure consistent application of the algorithm any ICs identified as artifacts were removed from the data. Table 5.1 below exhibits the number of ICs removed for each participant.

Participant	ICs removed
P1	21
P2	20
P3	22
P4	19
P5	16
P6	23
P7	22

Table 5.1. Exhibits the ICs removed for each participant based on SASICA identification of ICs as artifacts.

Following the ICs rejection, the data were epoched using a time-window leading up to the stone release (from -6000 ms to 0 ms, where 0 indicates the time of the stone release). Epochs were visually inspected and epochs presenting obvious artifacts were discarded from further analysis. Baseline correction was carried out by dividing the EEG data of interest by the equivalent power during the baseline period, scaled as a percentage change (%). The timing information provided by the manual trigger sent when the athlete pushed out of the hack could be used as an indicator of when the curlers started the delivery of the stone phase. Thus, by using the information provided by the first manual trigger, we calculated an appropriate baseline period, prior to that period. Based on the information provided by the first manual trigger we calculated that an appropriate baseline period would be -6000ms to -5000ms prior to the stone release. Table 5.2 below exhibits the average time (averaged across all 64 pushes for each individual curler) each curler pushed out of the hack prior to stone release based on the information provided by the first manual trigger.

Participant	Average time(s)
P1	3.65s
P2	3.22s
P3	3.63s
P4	3.67s
P5	3.68s
P6	3.49s
P7	3.53s

Table 5.2. Exhibits the average time (seconds) calculated for each participant at which each curler pushed out of the hack prior to releasing the stone.

In addition, the timing information provided by the first trigger (pushing out of the hack) was used to determine an appropriate period of interest to characterise processing. The timing information suggests that it should be possible to examine pre-shot activity from -2000ms to 0. The reasoning for not using a larger epoch (e.g., starting from -4000ms to 0) was that the EEG data were contaminated by muscle artifacts between -4000ms and -3000ms, which was the period of movement at which the curlers would push out of hack to start sliding down the ice. The movement during this period caused noise which contaminated the EEG data, thus the -4000ms to -3000ms period had to be discarded and not included in the final analysis.

To explore the spectral dynamics of the data over time, a time-frequency analysis was conducted through the convolution of Morlet wavelets (9 cycles at the lowest frequency and a maximum of 32 cycles at 40Hz for the highest frequency) across the epoch. Event-Related Spectral Perturbations (ERSP) were computed by normalizing Event-Related Spectra by dividing the power in the period of interest by power in the baseline period on a single trial basis (the choice of baseline is discussed in detail below). Event-Related Spectral Perturbations can be regarded as a generalization of the ERD/ERS analysis. The ERSP measures average dynamic changes in the amplitude of any given on-going EEG frequency as a function of time (relative to the experimental event of interest – in this case, the stone release). Overall, therefore, the ERSP measure reveals the average time course of relative changes in the EEG frequency spectrum (Makeig, 1993). To investigate neural power prior to the initiation of the stone release, EEG data were examined starting at 2 seconds prior to the stone release, based on the triggering markers acquired from the manual triggering (time-locked to the stone release). This 2 second epoch window was selected as this period was free of any visually observed muscle artifacts contaminating the EEG data.

Power relative to baseline values expressed as a percentage change (in %) were compared over time, between conditions, across *a-priori* defined frequency bands (Theta 4-7 Hz; Alpha 8-12 Hz; SMR 13-15 Hz; Beta 15-30 Hz) at electrodes sites in which visible differences underlying performance had been observed. Data from each frequency band was analysed independently using a within-subject repeated measures ANOVA. Given the focus on examining the effects of performance, any significant interactions involving performance were followed up by post-hoc t-tests. All analyses were carried out using a significance threshold of $p<0.05$, and any significant effects involving performance were followed up using paired sample t-tests (including Bonferroni correction for multiple comparisons where appropriate) to confirm whether performance related differences were reliable. Finally, to assess data quality and the choice of baseline period we examined variability in the baseline via the Root Mean Square (RMS, i.e., the arithmetic mean of the squares of a set of values). RMS was calculated independently for successful versus unsuccessful stones, across the entire baseline period, to determine any deviation in signal quality across conditions that might affect the interpretation of the results in the specific frequency bands. RMS was applied to all electrodes chosen to be analysed in this study, and examined for each participant individually, to provide insight into the overall quality of the EEG recording.

5.4 Results

5.4.1 Curling Behavioural Performance

To examine the overall pattern of stone delivery performance for each curler, successful stone delivery rates (%) were calculated across each block (total of 8 stones in each block) for each curler (Figure, 5.3).

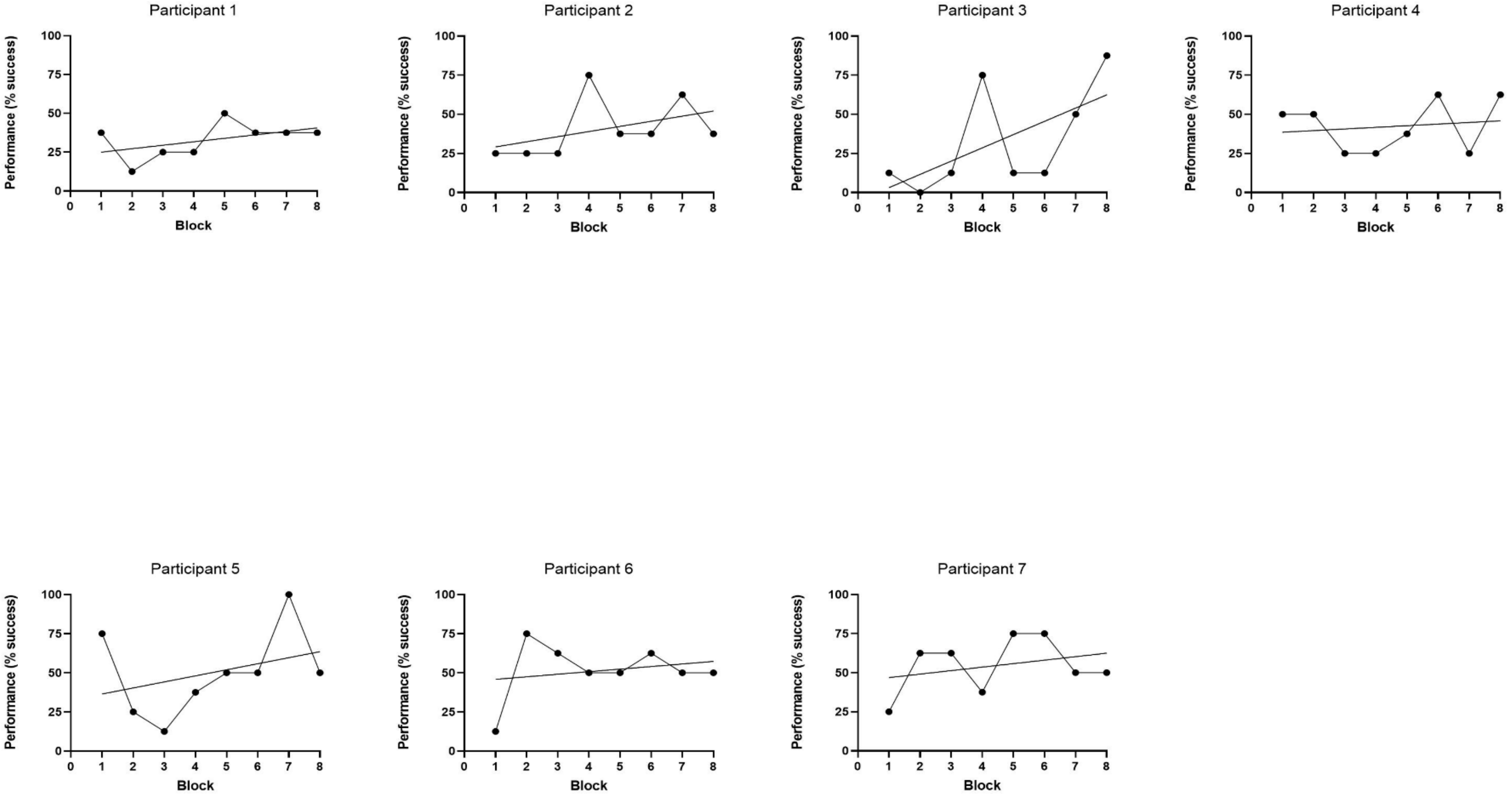


Figure 5.3. Exhibits the successful stone delivery rates (%) calculated for each participant for each block (8 stones in each bock).

Additionally, Figure 5.4 exhibits the average stone delivery rates (%) for each individual (average across all 64 stones). The information provided by Figure 5.4 can be used to explore the variability of our athletes around the group average (successful stone delivery rate %) -by examining the overall mean and standard deviation (as shown in Table 5.3). The average stone successful delivery rate was 43% and four athletes had achieved less than a 43% successful stone delivery. Although our group is considered homogenous as we are examining performance in expert athletes, as can be seen from Figures 5.3 and 5.4, and Table 5.3, in practice performance exhibits considerable variability both within and between individuals.

Participant	Mean (%)	Standard Deviation
1	32.81	11.4
2	40.62	18.6
3	32.81	33.3
4	42.18	16.2
5	50	27.5
6	51.56	18.2
7	54.68	17.5

Table 5.3. Mean (%) success rates for each participant averaged across all 8 blocks and associated standard deviations.

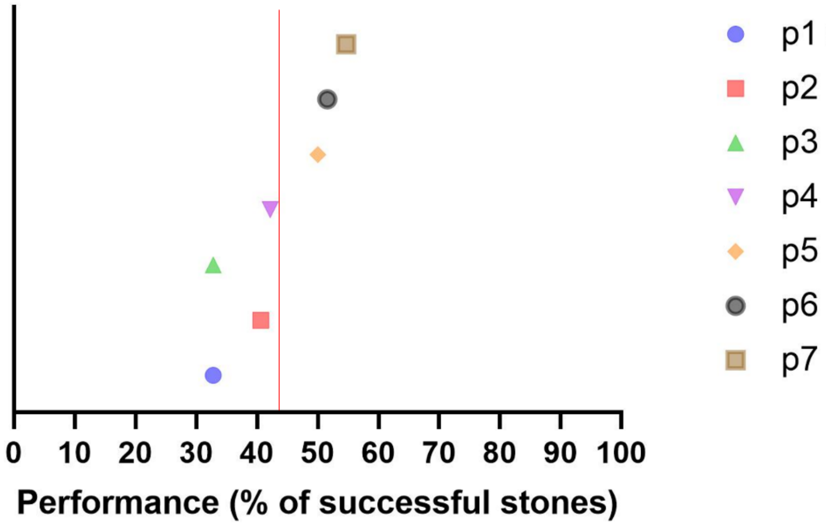


Figure 5.4. The figure exhibits the rate of successful stone delivery for each participant. The red line represents the mean successful stone deliver of the group (M=43%).

To explore the pattern of behaviour in more detail, curling performance was also assessed by examining stone distribution across individuals and blocks [i.e., the direction (in degrees) from the 4 feet circle] using circular statistics (analysed using Oriana Version 4, 2021). Circular statistics provide a visual representation of the mean distribution of shots around the target. This information is represented as a vector, with the location of the stone represented via the angular direction of the vector (blue line) and the mean resultant length of the vector (mean of stones-red line). The spread of the stones is reflected through the R value and circular variance. If all stone locations are in the same direction, the mean resultant vector will have a length close to 1, and the circular variance will be small. We performed the circular statistics by transforming the cartesian coordinates (reflecting the position of the stone relative to the button) into two dimensional vectors (distance and direction), which allowed the mean distance and direction to be calculated.

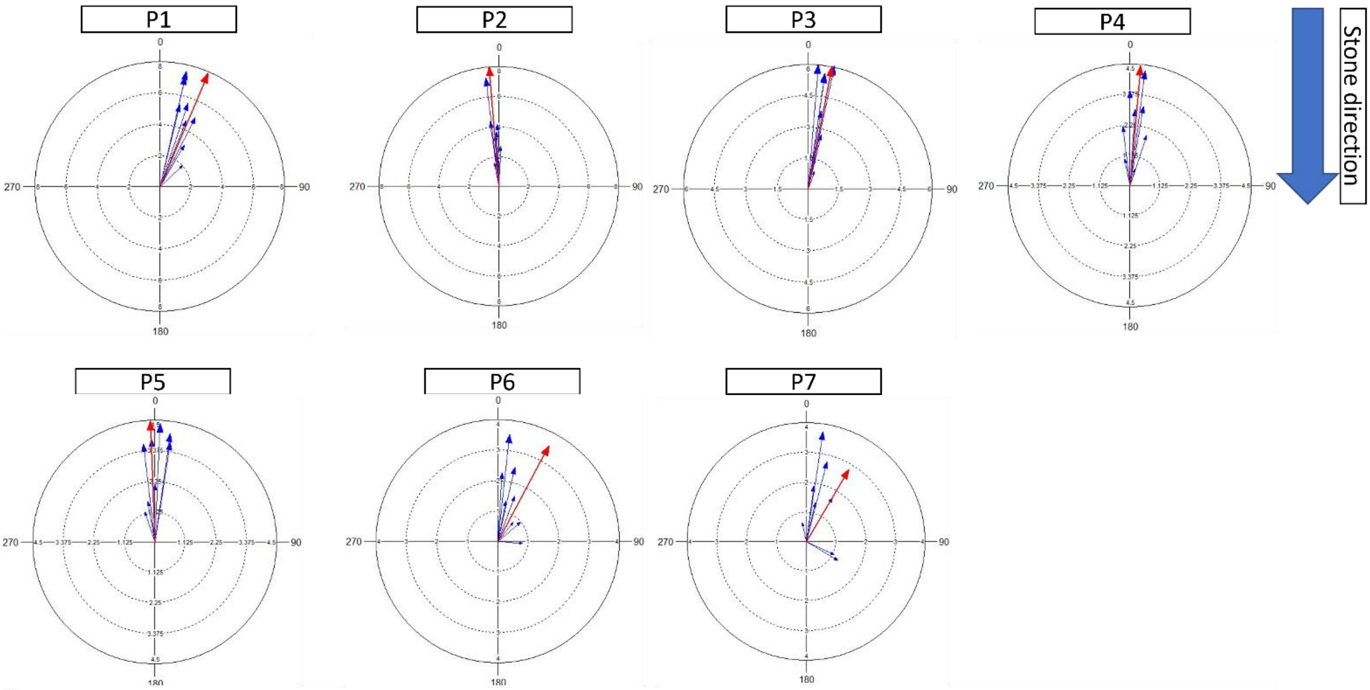


Figure 5.5. The figure presents the distribution of stone location (the centre of the graph represents the button, the y-axis 0˚-180˚separates short/long stone delivery and the x-axis 90˚-270 ˚separates the left/right stone delivery. Each plot represents the distribution of averaged stones for each block around the button, shown separately for each participant. The blue lines represent the blocks, and the red lines indicates the direction and magnitude of the mean resultant vector.

Figure 5.5 exhibits the overall average stone location (and average stone location for each block) for each participant. As seen in Figure 5.5, Participants 1-6 show highly consistent and homogenous behavioural profiles - suggesting reliable stone delivery. The data does, however, reveal quite distinct patterns across the curlers. For example, Participant 1's stone delivery profile suggests a consistent bias towards the left and short of the house, whereas Participant 2 is short of the house and on the right. By contrast Participant 5 appears to be most accurate, with no bias towards one side of the house. Furthermore, Participant 7 clearly exhibits greater variability, reflected in a more widespread stone distribution which is sometimes long of the house and on the left and sometimes short of those and on the right or left.

Overall, these data suggest that visual inspection of the athletes' performance using circular statistics does provide useful information about the approach being taken (e.g., identifying biases towards left or right, or in placing short or long), providing information that could potentially influence decisions about whether individual athletes should take part in competitions, or factoring into the design of training routines for practice. To formally assess if there were any differences in location across blocks a Watson-Williams test was used to compare the distribution of stones around the house within each participant. Each athlete was assessed individually to determine whether their delivery was consistent or variable across blocks. The analysis revealed no significant difference in the distribution of stone delivery for Participants 1 to 6 (all P's > 0.25), suggesting delivery was homogenous, with low levels of variability across blocks. By contrast, a significant difference in stone distribution between blocks was found for Participant 7 ($F(1,7) = 2.74$, $p = 0.01$), consistent with the impression provided by Figure 5.5.

To examine Participant 7 in more detail, we first examine the pattern of stone locations (Figure 5.7). Figure 5.7 exhibits the angular vectors (blue lines) that reflect the location of each stone relative to the button-within each block-and the mean resultant length vector (average of 8 stones within each block-red line) reflecting the spread of the stones. Table 5.4 exhibits the mean resultant vector, the length of the mean resultant vector and circular variance of the stones within each block.

Block	Mean Resultant Vector (Θ°)	R Length (0,1)	Variance (0,1)
1	60.75	0.40	0.59
2	342.62	0.27	0.72
3	129.00	0.51	0.48
4	11.29	0.50	0.49
5	103.69	0.49	0.50
6	35.20	0.34	0.65
7	30.81	0.58	0.41
8	17.76	0.75	0.24

Table 5.4. Properties of angular data for stone location, representing the mean resultant vector and R length and variance.

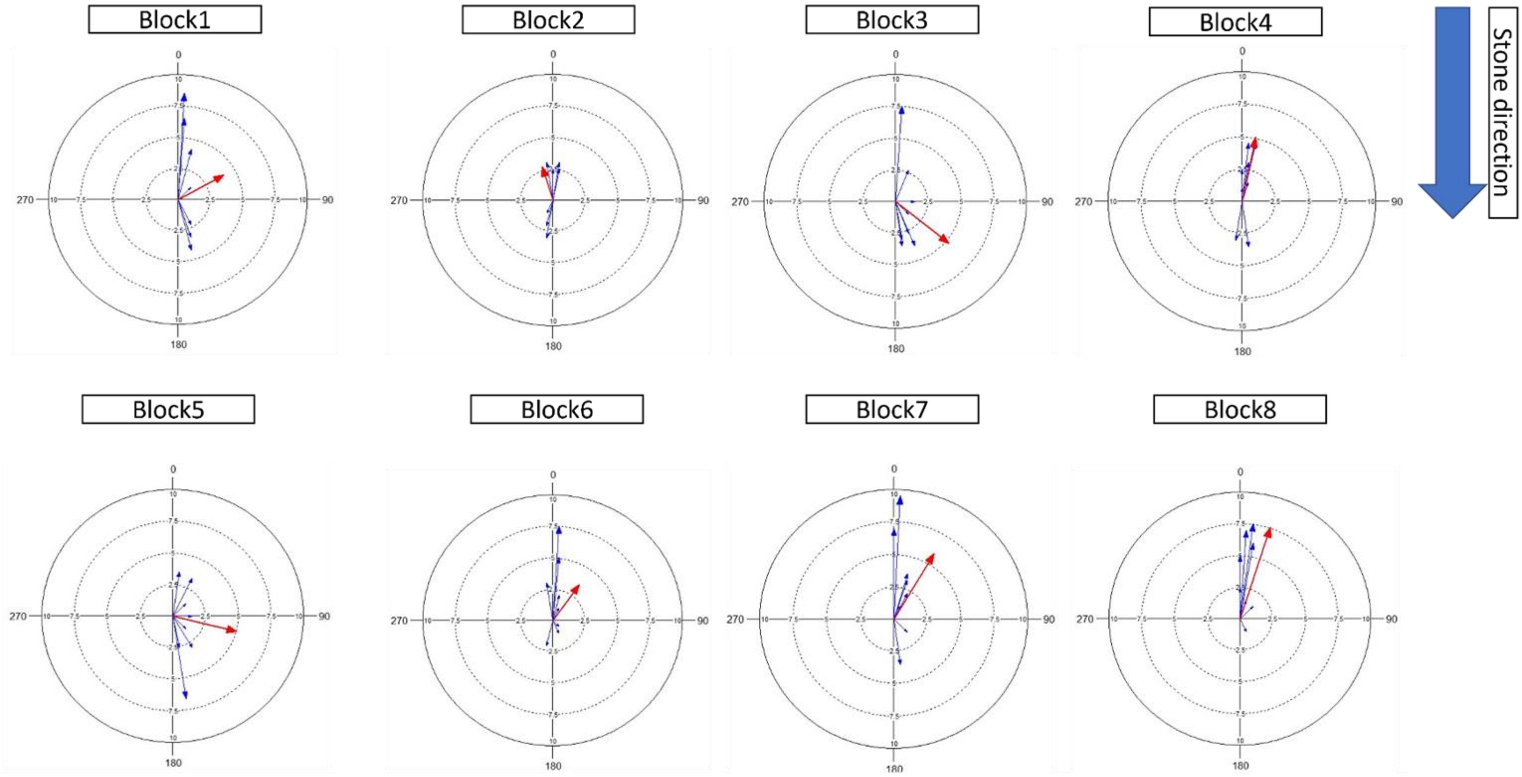


Figure 5.6. The figure presents the distribution of stone location for participant 7. Each plot represents the distribution of stones for each block around the button, shown separately for each block.

Post-hoc pairwise comparisons between blocks 1-8 for Participant 7 revealed that the distribution of stones (mean resultant vector) was significantly different between blocks 2 and 5 [F(1,14)=5.72, p=0.03], blocks 3 and 7 [F(1,14)=7.54, p=0.01], blocks 3 and 8 [F(1,14)=12.39, p=0.003], blocks 4 and 5 [F(1,14)=5.69, p=0.03] and between blocks 5 and 8 [F(1,14)=7.33, p=0.01]. As can be seen Figure 5.6 the mean resultant vector for block 2 is short of the house and on the right, compared to block 5 which is on the left and long from the house. By contrast, in block 3 the mean resultant vector (red arrow) is long and on the left, compared to blocks 7 and 8 where the vector is short and, on the left, with greater variability (as indicated by the increased length of the red line in blocks 7 and 8). Additionally, block 4 and block 5 are different as the mean resultant vector for block 4 lies short and on the left compared to block 5 that lies long and on the left. Block 5 and block 8 are different as the mean resultant vector for block 5 lies long and on the left whereas for block 8 it lies short and on the left. A long stone would mean that the stone travels further away from the house and a short stone would mean that the stone is closer to the curler and shorter from the house.

As the proceeding analysis makes clear circular statistics provide a powerful way to represent performance. Nonetheless it is important to recognise that these data must be interpreted within the wider context of the game. For example, coaches may purposefully select players who consistently produce left- or right-sided shots depending on who is being played against; similarly, the curler may alter their strategy as a game develops, moving from shorter to longer shots across a block of shots. Whether variability is considered desirable, or problematic will of course depend on the strategy and approach of the individual athlete and coach. In the current context the behavioural data suggest that most of our curlers exhibited a homogenous stone distribution profile (consistent with their status as elite athletes). The single exception was Participant 7, who exhibited considerable variability across blocks. Our athletes were asked to be as accurate as possible on every shot, and in this context the lack of consistency would be viewed as problematic. If this data was being used to select athletes for competition, Participant 7 would have been unlikely to play.

5.4.2 EEG Analysis

5.4.3 Time-Frequency Analysis

To provide an overview of changes in EEG power throughout the stone delivery phase scalp maps for alpha (8-12 Hz), theta (4-7 Hz), beta (15-30 Hz) and SMR (13-15 Hz) power across the two second period prior to releasing the stone were generated, characterising the pattern of effects for successful and unsuccessful performance. Identified patterns of neural activity from the scalp maps were followed up with time-frequency plots illustrating the neural pattern of activity. Before presenting the outcomes of statistical analysis focused on each frequency band, we first describe the pattern of effects shown within the scalp maps and time frequency plots.

5.4.4 Alpha (8-12 Hz)

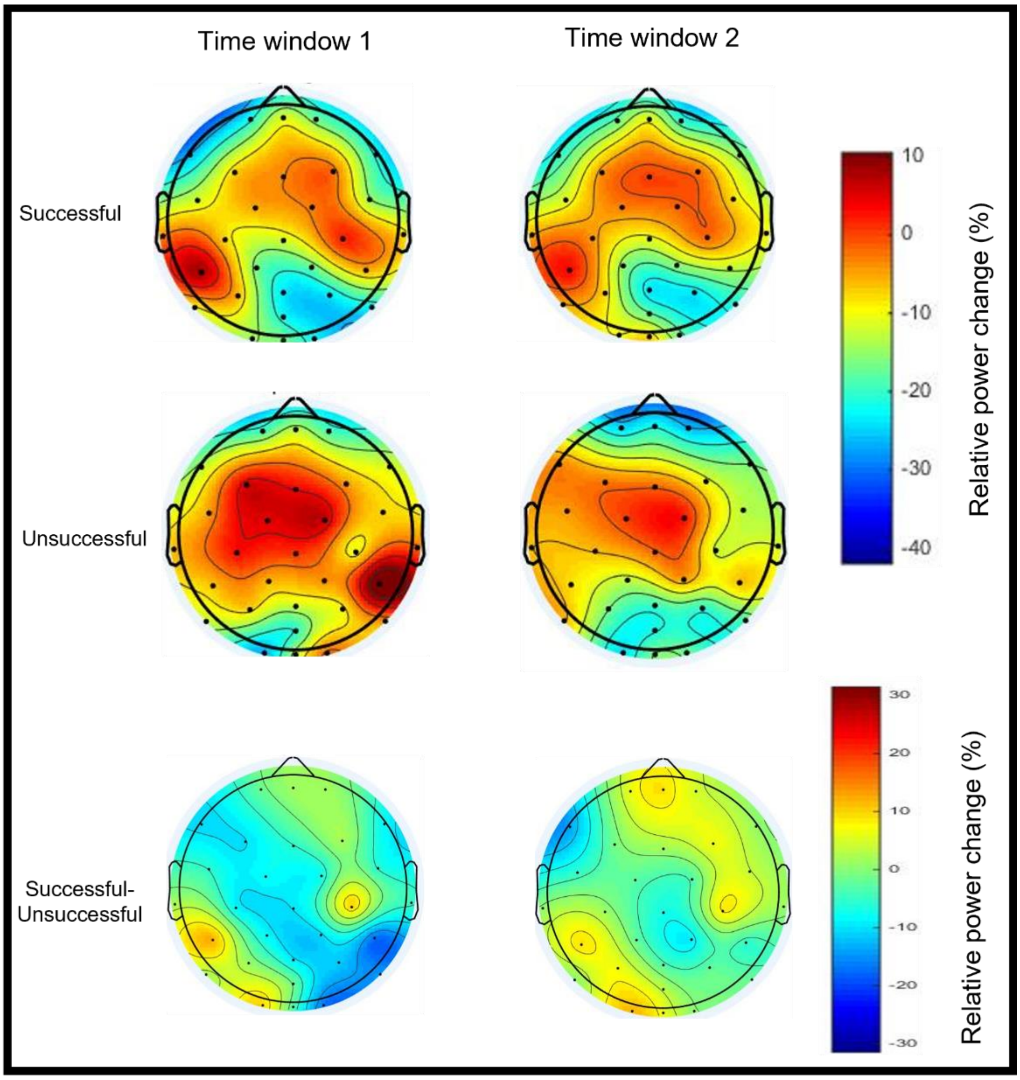


Figure 5.7. Topographical maps representing alpha activity (8-12 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.7, there is a clear pattern of alpha activity exhibited in the difference scalp maps, underlying successful performance during time windows 1 (-2000ms to -1000ms) and 2 (-1000ms to 0). Notably, there is a larger focal increase of alpha power in successful performance compared to unsuccessful performance over left centro-parietal areas. Interestingly, the opposite pattern is observed over lateral primary motor areas, i.e., larger increase of alpha power in successful performance over right primary motor areas (C4) and larger increase of alpha power in unsuccessful performance over left primary motor areas (electrode C3).

Initial analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (CP5/CP6). Despite the impression provided in Figure 5.7, it is notable that the analysis did not reveal any significant interactions with time or electrodes (all p’s > 0.09). Additionally, analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (C3/C4). Despite the impression provided in Figure 5.7, it is notable that the analysis did not reveal any significant interactions with time or electrodes (all p’s > 0.33).

As no significant main effects or interactions have been revealed when the analysis examined the pattern of effects during the two second time window leading up to the stone release, follow up analysis was employed to better target the effects identified from the visual examination of time frequency plots. To increase the likelihood of capturing the effects that are visible in the time frequency plots (where the effects are often relatively short lived) the targeted analysis employed shorter and more targeted time windows. This approach was replicated across frequency bands (if needed), and we report results that have exhibited significant differences. The following targeted analysis will be carried out by using the standard frequency bands as examined in the initial analysis.

Additional Targeted Analysis for Alpha activity (8-12Hz)

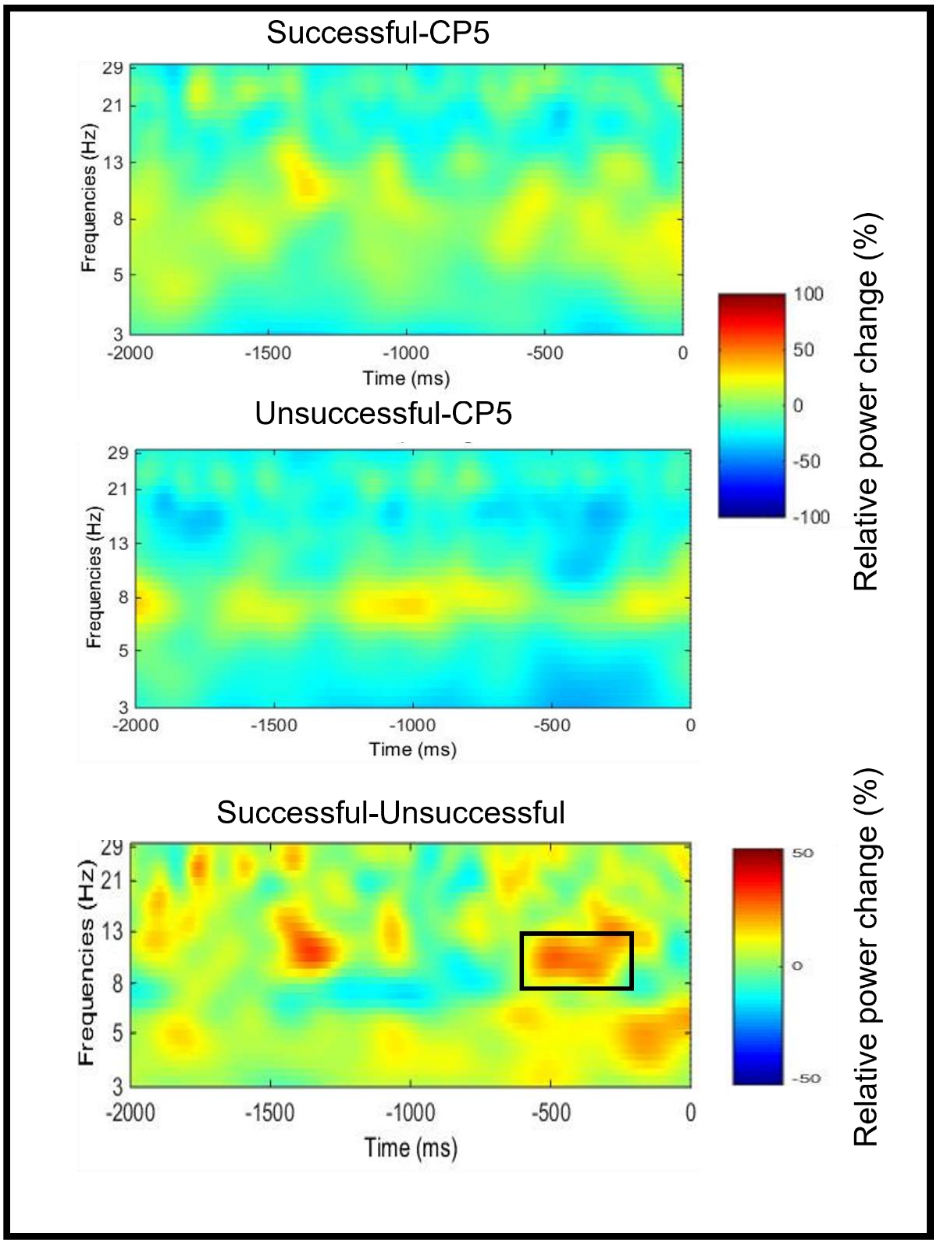
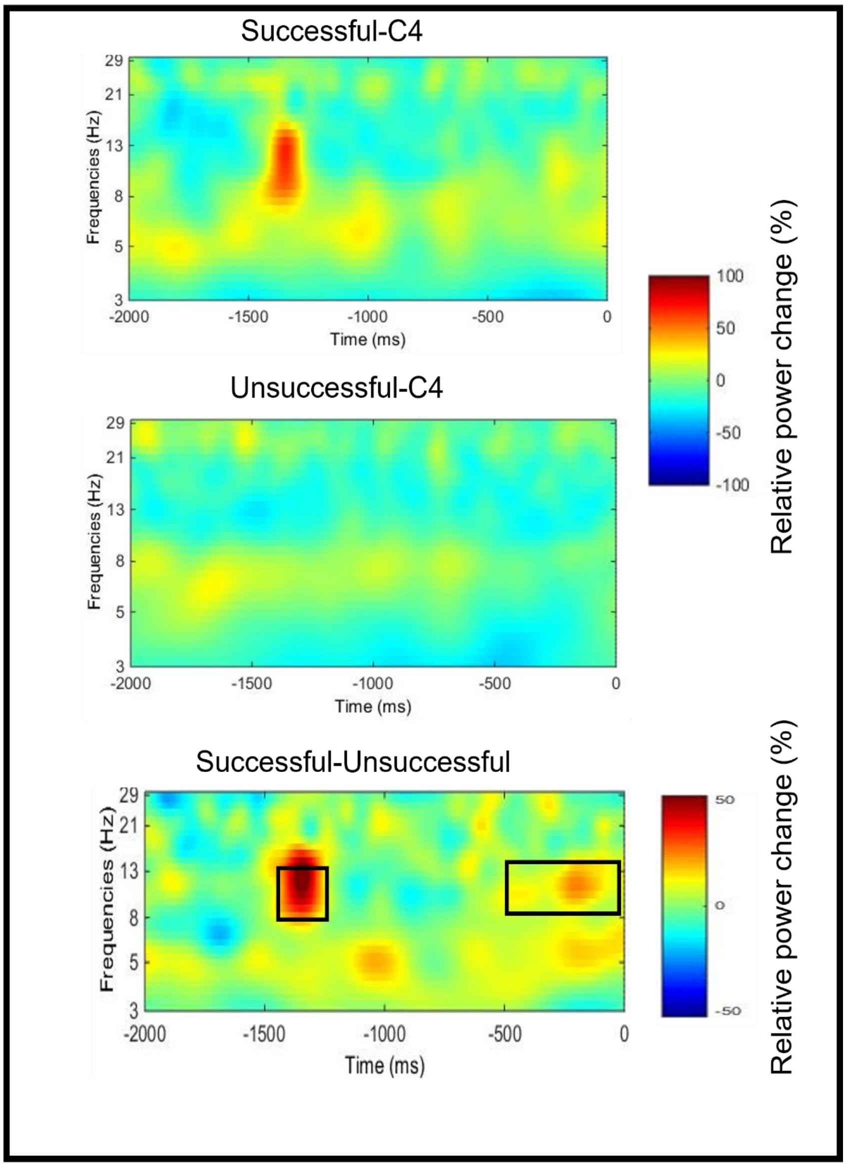


Figure 5.8. The time frequency plots exhibit the neural activity at CP5 electrode across frequencies in the 2 second period of interest. Zero indicates the time of the stone release. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful-unsuccessful. The black square represents the difference between successful-unsuccessful performance. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Evident in the time frequency plot (Figure 5.8), there is a difference in alpha activity characterizing the two levels of performance, with more alpha activity underlying successful compared to unsuccessful performance at around -600ms to -300ms. A paired samples t-test was conducted to compare alpha activity (8-12 Hz) for successful and unsuccessful shots, from -600ms to -300ms, at CP5 electrode. The analysis revealed a significant difference [t(6)=7.10,p<0.001] between the two levels of performance within the alpha frequency range (8-12Hz), with more alpha activity underlying successful (M=10.68) compared to unsuccessful (M=-20.94) performance.


Successful-C4

Unsuccessful-C4

Successful-Unsuccessful

Figure 5.9. The time frequency plots exhibit the neural activity at C4 electrode across frequencies in the 2 second period of interest. Zero indicates the time of the stone release. Successful and unsuccessful performances are exhibited in the first two plots, the third plot exhibits the difference of successful-unsuccessful. The black square represents the difference between successful-unsuccessful performance. The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

Evident in the time frequency plot (Figure 5.9), there is a difference of alpha activity characterizing the two levels of performance, with more alpha activity underlying successful compared to unsuccessful performance at around -1500ms to -1300ms, and from -500ms to 0, at the C4 electrode. A paired samples t-test was conducted to compare successful and unsuccessful performance (8-12 Hz), between -1500ms and -1300ms, at the C4 electrode. The analysis did not reveal a significant difference [t(6)=1.38,p=.21] between the two levels of performance within the alpha frequency range (8-12Hz). Another paired samples t-test was conducted to compare successful and unsuccessful performance within alpha activity (8-12 Hz) between -500ms and 0ms, again at C4 electrode. This analysis did not reveal a significant difference [t(6)=2.03,p=.08] between the two levels of performance within the alpha frequency range (8-12Hz).

5.4.5 Low Alpha (8-10 Hz)

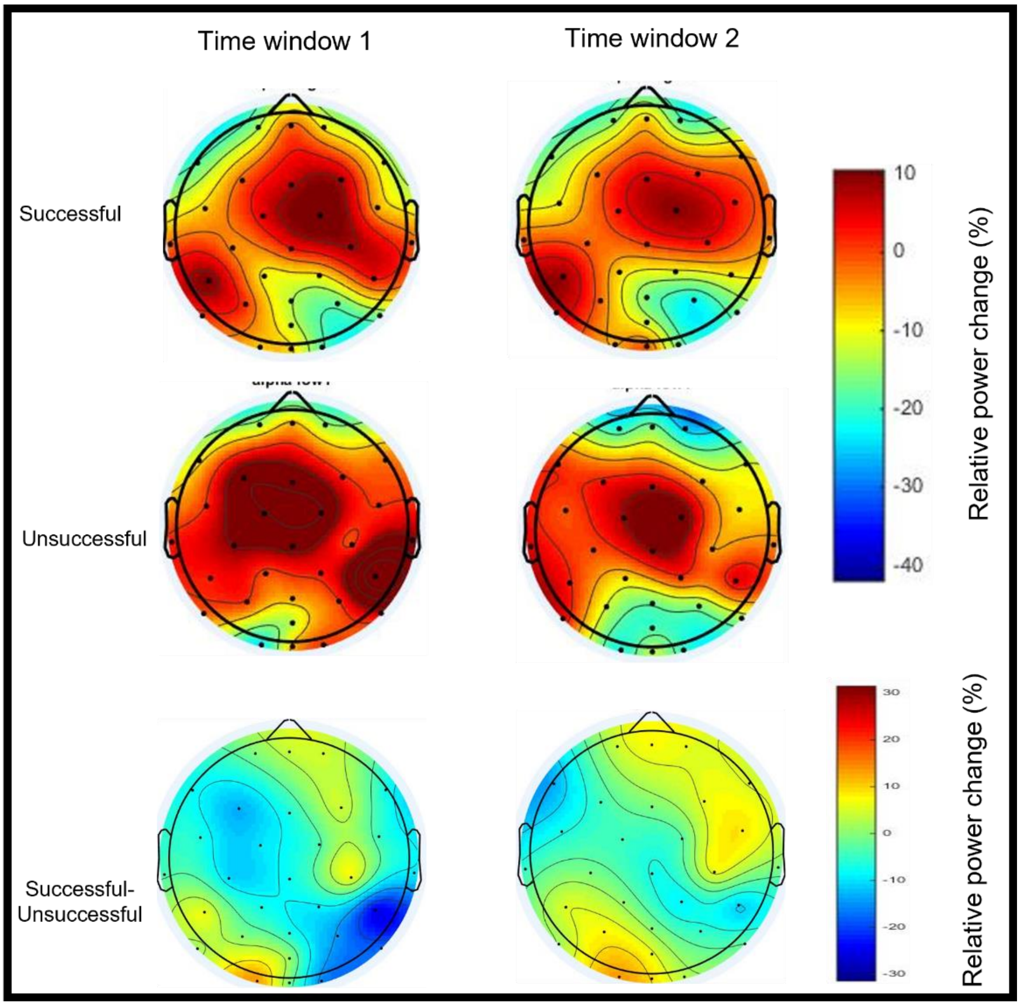


Figure 5.10. Topographical maps representing alpha activity (8-10 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.10, the topographical patterns of low alpha (8-10Hz) power are to a large extent similar to those of the entire alpha power spectrum (i.e. 8-12Hz).

Initial analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (CP5/CP6). Despite the impression provided in Figure 5.10, the analysis did not reveal any significant interactions with time or electrodes (all p’s > 0.22). Additionally, analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (C3/C4). Despite the impression provided in Figure 5.10, the analysis did not reveal any significant interactions with time or electrodes (all p's > 0.26).

Additional Targeted Analysis for Low Alpha Activity (8-10Hz)

Evident in the time frequency plot (Figure 5.8), there is a difference of alpha activity characterizing the two levels of performance, with more alpha activity underlying successful compared to unsuccessful performance at around -600ms to -300ms. A paired samples t-test was conducted to compare successful and unsuccessful performance within low alpha (8-10 Hz), from -600ms to -300ms, at the CP5 electrode. Confirming the impression provided by Figure 5.11, this analysis revealed a significant difference [t(6)=4.81,p=0.003] between the two levels of performance within the low alpha frequency range (8-10 Hz), with more low alpha activity underlying successful (M=15.42%) than unsuccessful (M= -14.93) performance. Evident in the time frequency plot (Figure 5.9), there is a difference of alpha activity characterizing the two levels of performance, with more alpha activity underlying successful compared to unsuccessful performance at around -1500ms to -1300ms. A paired samples t-test was conducted to compare successful and unsuccessful performance within low alpha (8-10 Hz), between -1500ms and -1300ms, at the C4 electrode. Despite the impression provided by Figure 5.9, this analysis did not reveal a significant difference [t(6)=1.33,p=.23] between the two levels of performance within the low alpha frequency range (8-10 Hz). A paired samples t-test was also conducted to compare successful and unsuccessful performance within low alpha activity (8-10 Hz), between -500ms and 0ms, at the C4 electrode. Contrary to the impression provided by Figure 5.9 this analysis did not reveal a significant difference [t(6)=1.46,p=.19] between the two levels of performance within the low alpha frequency range (8-10 Hz).

5.4.6 High Alpha (10-12 Hz)

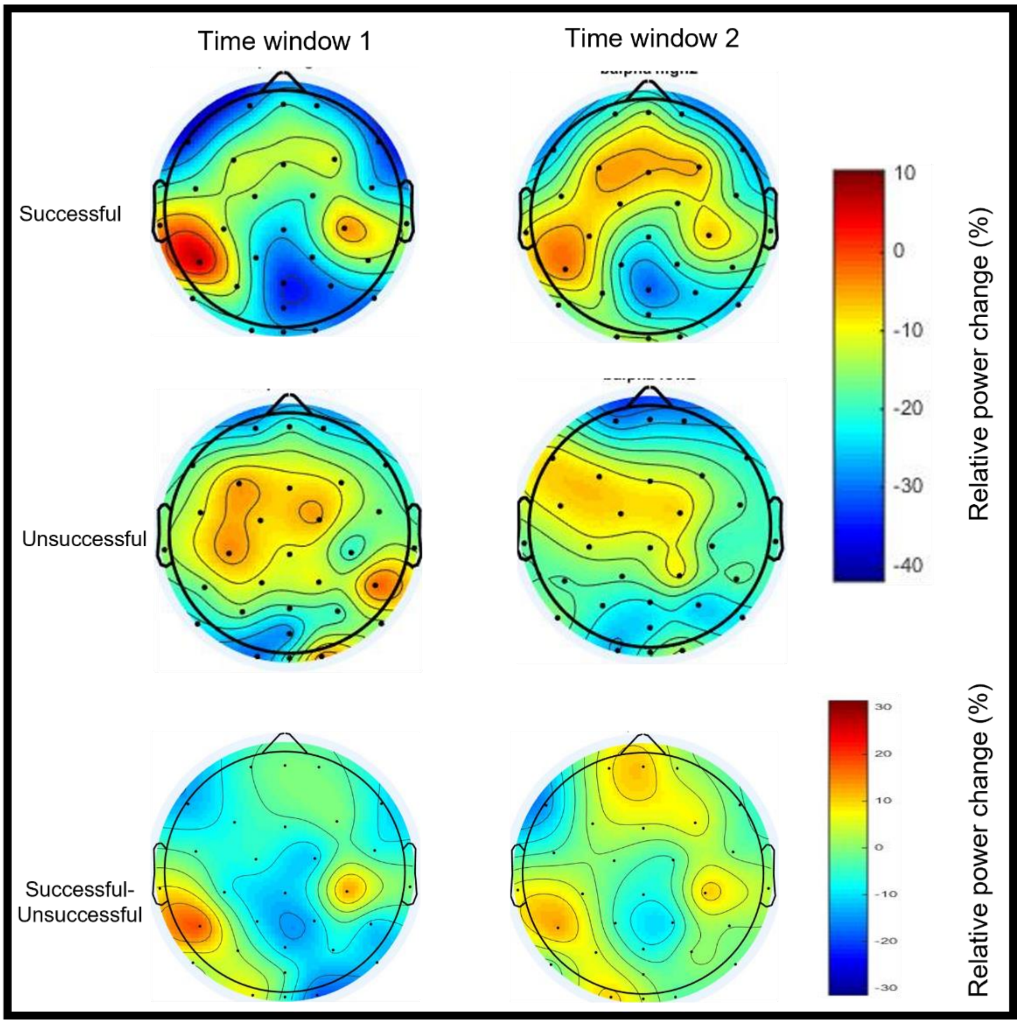


Figure 5.11. Topographical maps representing alpha activity (10-12 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.11, although the mid frontocentral increase, which was evident in the low alpha (8-10Hz) scalp mas is almost absent in high(10-12Hz) alpha, the overall pattern, evident in the difference scalp maps remains the same.

Initial analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (CP5/CP6). Despite the impression provided in Figure 5.11, the analysis did not reveal any significant interactions with time or electrodes (all p’s > 0.27). Additionally, analysis of the data examined the overall pattern of effects using repeated measures (2 x 2 x 2) ANOVA with factors of Performance (successful/unsuccessful), Time (T1/T2) and Electrode (C3/C4). Despite the impression provided in Figure 5.11, the analysis did not reveal any significant interactions with time or electrodes (all p’s > 0.53).

Additional Targeted Analysis for High Alpha Activity (10-12Hz)

Evident in the time frequency plot (Figure 5.8), there is a difference of alpha activity characterizing the two levels of performance, with more alpha activity underlying successful than unsuccessful performance at around -600ms to -300ms. A paired samples t-test was conducted to compare successful and unsuccessful performance within high alpha (10-12 Hz), from -600ms to -300ms, at the CP5 electrode. This analysis revealed a significant difference [t(6)=6.33,p<0.001] between the two levels of performance within the high alpha frequency range (10-12 Hz), with more activity underlying successful (M=5.94%) compared to unsuccessful (M= -26.95%) performance, consistent with the impression provided by Figure 5.8.

Evident in the time frequency plot (Figure 5.9), there is also a difference in high alpha activity characterizing the two levels of performance from around -1500ms to -1300ms, with more alpha activity underlying successful compared to unsuccessful performance . A paired samples t-test was conducted to compare successful and unsuccessful performance within high alpha (10-12 Hz), from -1500ms to -1300ms, at C4 electrode. Contrary to the impression provided by Figure 5.9 this analysis did not reveal a significant difference [t(6)=1.30,p=.24] between the two levels of performance within the high alpha frequency range (10-12 Hz). A paired samples t-test was also conducted to compare successful and unsuccessful performance within high alpha activity (10-12 Hz) between -500ms and 0ms, at C4 electrode. In this case the analysis revealed a significant difference [t(6)=2.44,p=.05] between the two levels of performance within the high alpha frequency range (10-12 Hz), with more activity underlying successful (M=5.06%) compared to unsuccessful (M=-17.85%) performance.

5.4.7 Theta Activity (4-7 Hz)

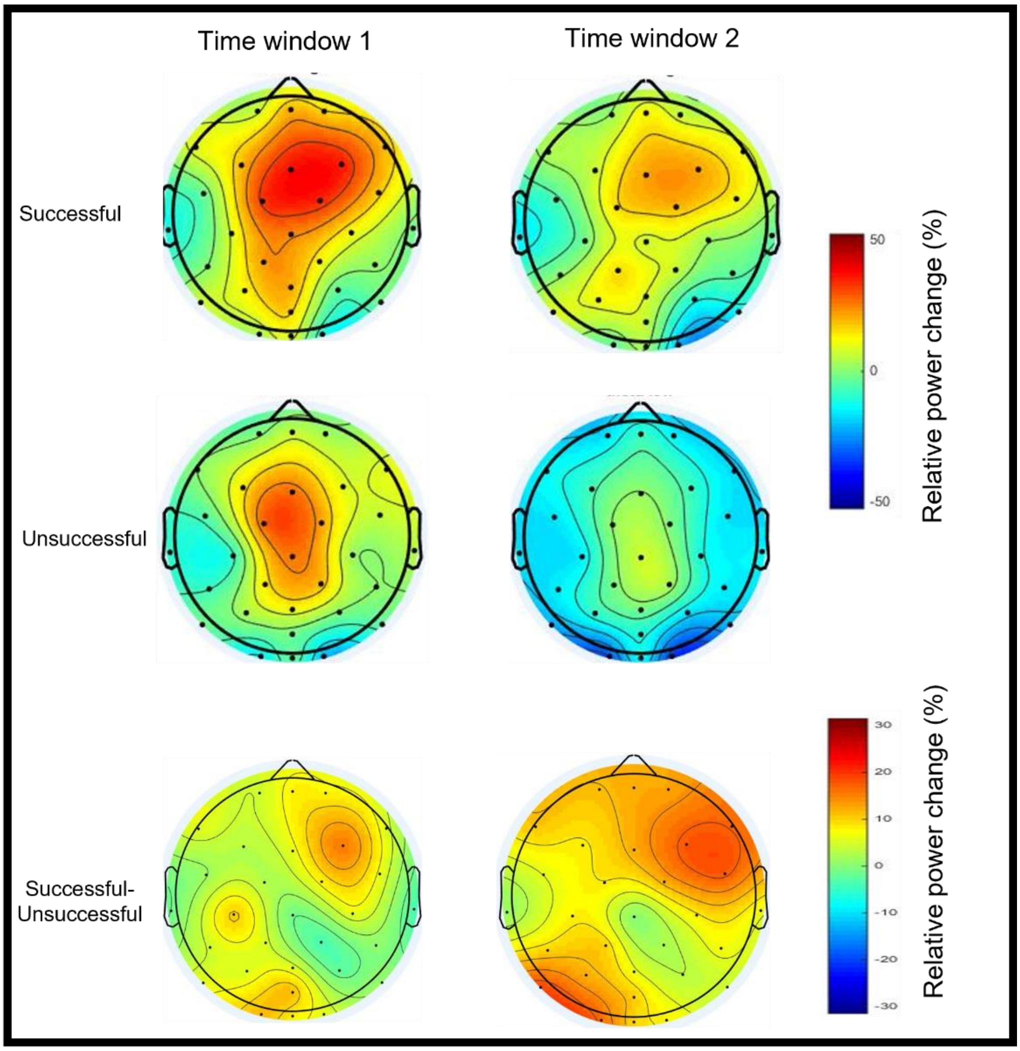


Figure 5.12. Topographical maps representing theta activity (4-7 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.12 there appears to be an increase in theta activity underlying successful compared to unsuccessful performance, evident in the topographic maps as a maxima over right frontal-central electrodes F4/FC6 during the two time windows of interest (two second time window prior to the release of the stone). The topographic maps suggest that the changes in theta are largest at the right frontal-central region, reflected in the large positive peak over F4/FC6 electrodes in the successful topographical map. Analysis of these data examined the observed pattern of effects using a 2 by 2 ANOVA with factors of performance (successful/unsuccessful) and time (T1/T2), averaged across the F4 and FC6 electrodes. The analysis revealed a significant main effect of performance [F(1,6)=9.88,p=.02], reflecting the fact higher theta for successful (M=26.11%) than unsuccessful (M=5.74%) performance - in line with the impression provided in the topographical maps.

5.4.8 Beta Activity (15-30 Hz)

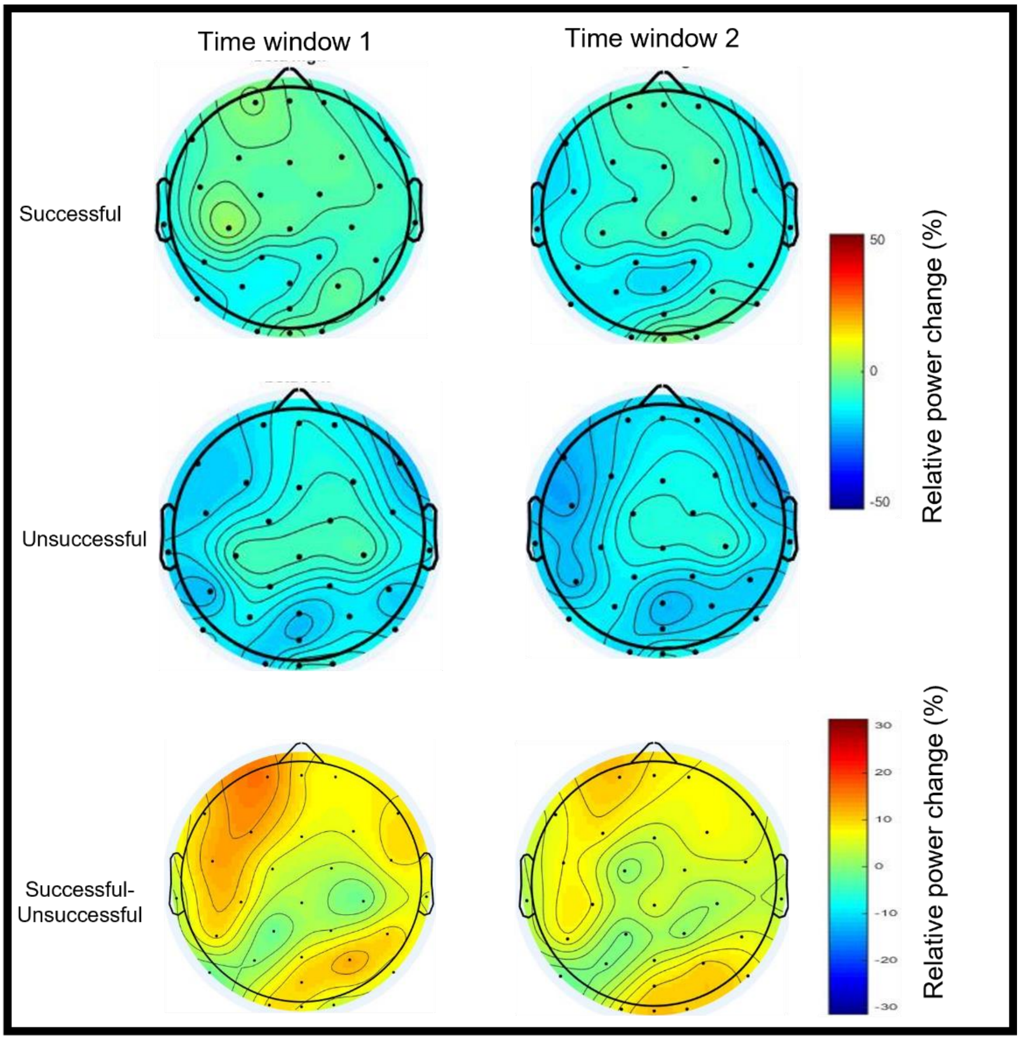


Figure 5.13. Topographical maps representing beta activity (15-30 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.13 the topographic maps suggest that there are changes in beta activity underlying unsuccessful compared to successful performance. Successful shots are associated with an increase in beta over central electrodes over the two-time second period prior to releasing the stone. Initial analysis of the data examined the observed pattern of effects using 2 by 2 ANOVA with factors of performance (successful/unsuccessful) and time (T1/T2), averaged across the C3, CZ and C4 electrodes. The analysis did not reveal any significant main effects or an interaction, suggesting that beta power did not differ as a function of performance.

5.4.9 SMR Frequency (13-15 Hz)

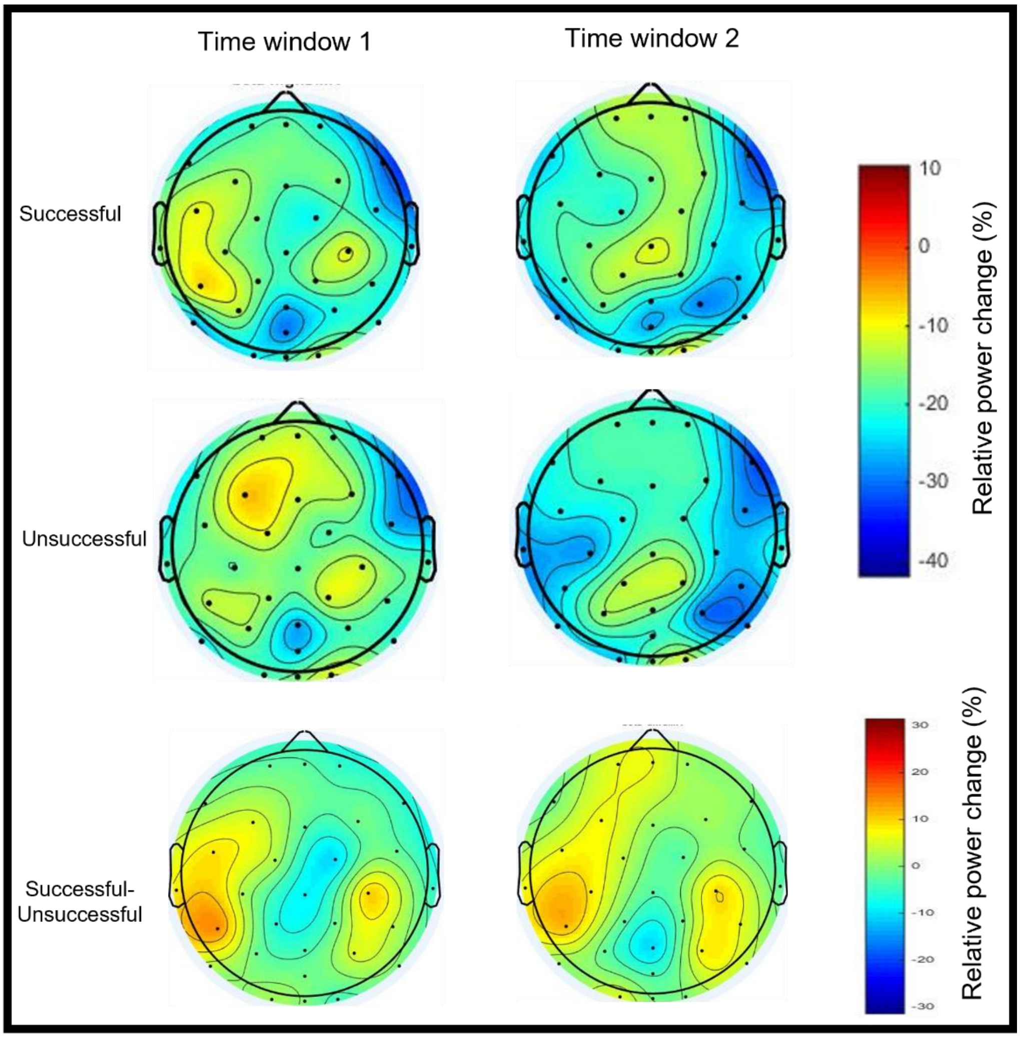


Figure 5.14. Topographical maps representing SMR activity (13-15 Hz) for successful and unsuccessful performance over the two-time windows. The last row represents the difference between the two conditions (successful-unsuccessful). The scaling represents the relative power change (%) from baseline, with red indicating an increase and blue indicating a decrease.

As can be seen in Figure 5.14 the topographic maps suggest that there are small differences in SMR activity underlying unsuccessful compared to successful performance over the two-time second period of interest, prior to releasing the stone. Successful and unsuccessful shots are associated with a decrease in SMR power over central electrodes. Successful shots are associated with a smaller decrease in SMR over central electrodes. Initial analysis of the data examined the observed pattern of effects using 2 by 2 ANOVA with factors of performance (successful/unsuccessful) and time (T1/T2), averaged across the C3, CZ and C4 electrodes. The analysis did not reveal any significant main effects or an interaction, suggesting that SMR activity did not differ with performances.

5.4.10 Root Mean Square (RMS)

One of the aims of this study was to explore whether the differences in neural activity underlying successful and unsuccessful performance are due to the selection of the baseline period. To our knowledge this is the first study investigating neural activity within a curling task, thus as a check on the suitability of our choice of baseline period (-6000ms to -5000ms), we examined variability in the baseline period using the Root-Mean-Square measure. In the wider EEG literature RMS is considered to be a useful measure to explore noise in the baseline, (Kappenman & Luck, 2010) and within the frame of this PhD this measure it is used to compare the amount of noise across recording conditions, to establish the impact of residual noise on the period of interest examined.

5.4.10.1 Estimation of baseline residual noise

Figure 5.15, 5.16 and 5.17 exhibit the RMS in the baseline period activity at the F4/FC6, C4 and CP5 electrodes respectively for each individual participant.

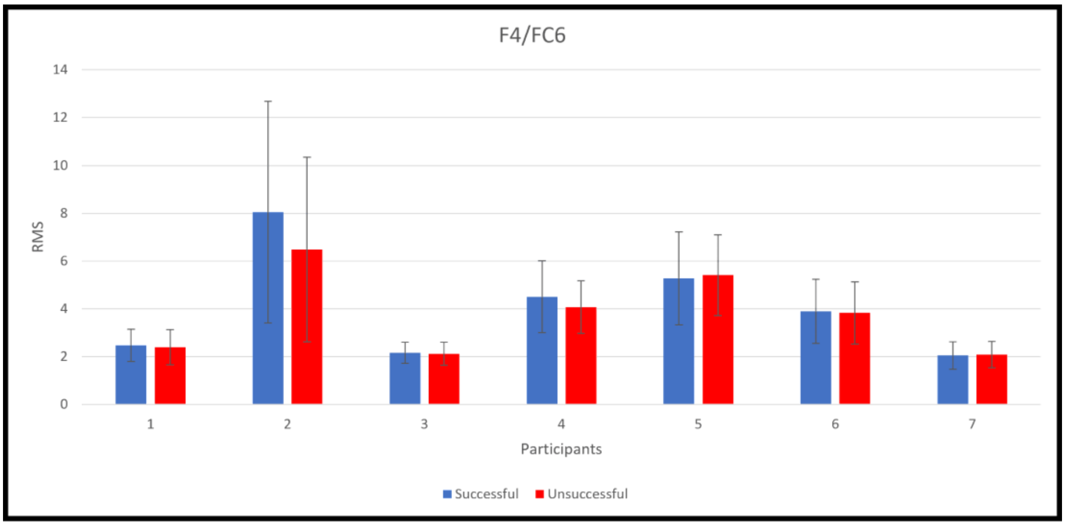


Figure 5.15.Root Mean Square (RMS) of the baseline period activity (-6000ms to -5000ms) averaged across F4/FC6 electrodes across participants for successful (blue) and unsuccessful (red) performance.

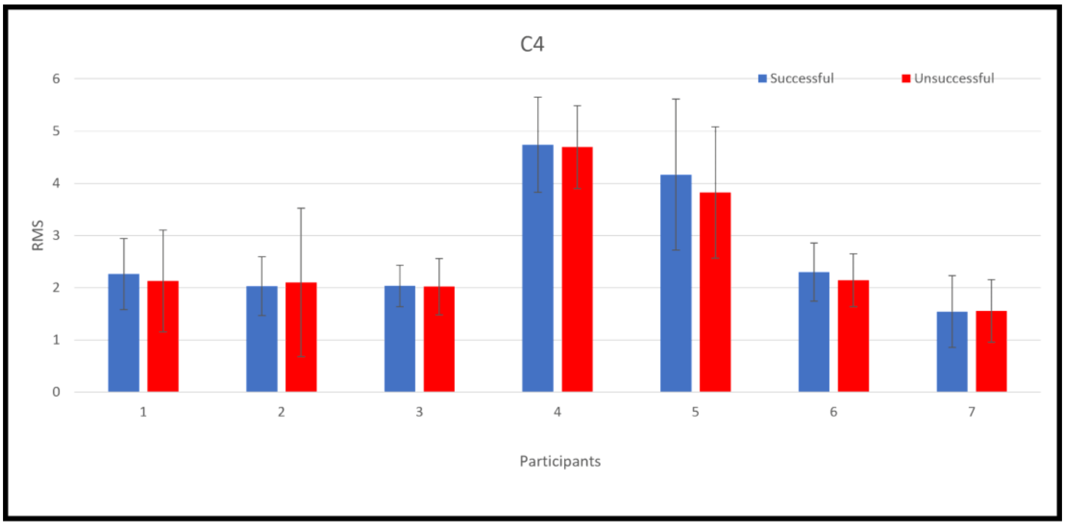


Figure 5.16.Root Mean Square (RMS) of the baseline period activity (-6000ms to -5000ms) averaged across C4 electrodes across participants for successful (blue) and unsuccessful (red) performance.

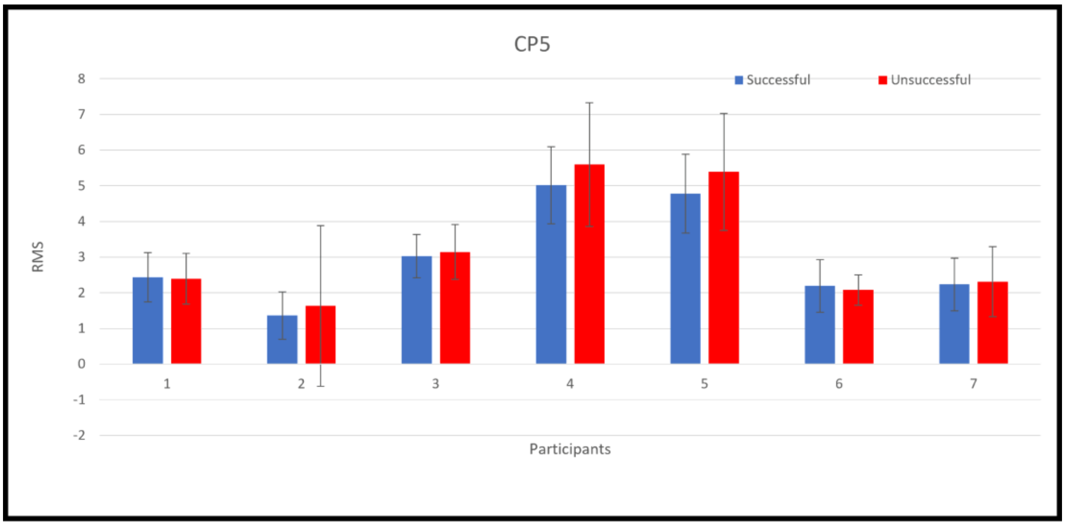


Figure 5.17.Root Mean Square (RMS) of the baseline period activity (-6000ms to -5000ms) averaged across CP5 electrodes across participants for successful (blue) and unsuccessful (red) performance.

As seen in Figures 5.15 to 5.17, no significant differences can be detected overall across electrodes and participants between successful and unsuccessful performance in the baseline period. Overall, the magnitude of activity associated with successful and unsuccessful performance does not appear to differ in the baseline period activity. Paired samples t-tests were performed for each region individually, to examine if there were any reliable differences in the baseline period between successful and unsuccessful performance. At F4/FC6 there was no significant difference in the baseline period activity RMS between successful (M=4.06; SD=2.15) and unsuccessful (M=3.77; SD=1.71) performance [t(6)=1.29,p=.24]. Similarly, at C4 there was no significant difference in the baseline period activity RMS between successful (M=2.72; SD=1.21) and unsuccessful (M=2.63; SD=1.15) performance [t(6)=1.67,p=.14]. And similarly at CP5 there was also no significant difference in the baseline period activity RMS between successful (M=3.00; SD=1.38) and unsuccessful (M=3.22; SD=1.61) performance [t(6)=-2.00,p=.09].

5.5 Discussion

To our knowledge the current study is the first to examine neural activity underlying successful versus unsuccessful curling performance in an ecologically valid setting (on an ice curling arena). We collaborated with athletes and coaches to develop an *in situ* curling task that did not interfere with the practice routine of our athletes. Our approach to EEG data analysis was necessarily exploratory because no previous literature has ever investigated neural activity during curling. To allow comparison with the pre-shot effects observed in other sports, we examined neural activity during a two second period leading up to the release of the stone and independently examined distinct frequency bands. Our analyses revealed statistically significant differences in EEG signals between successful and unsuccessful performance, confirming that statistically reliable effects were present for specific frequency bands, at specific time windows. The results revealed differences in the neural activity associated with successful and unsuccessful stone delivery - EEG effects that differed both temporally and topographically across frequency bands.

Below we discuss the identified effects in detail, highlighting what the pattern of effects suggests about the cognitive basis of successful performance in curling. First, however, we acknowledge limitations in the approach adopted here. As the first study to investigate differences in neural activity within a curling task in elite athletes our approach to the analysis of the data was heavily data driven - there was no a priori literature to inform the choice of time windows or electrodes. It is notable that this approach led to a more fine-grained temporal assessment than in previous chapters - rather than sticking to regular 1 second time windows, the analysis was informed by visual inspection of the data, resulting in bespoke time windows. Furthermore, because of the timing of the data collection in the different sports, the approach adopted here did not include the Individual Alpha Peak Frequency (IAPF) method outlined in Chapter 4 - suggesting that the pattern of results may differ somewhat when a more individually tailored IAPF analysis is employed. Taken together these methodological limitations suggest some caution is required in the interpretation of the EEG findings - and more importantly, perhaps, that future replications of the findings are required.

As noted in the introduction to this chapter, curling occupies a unique and important place in the Scottish sporting domain. According to an article (Set in Stone, 2017) published by SportScotland, curling has delivered multiple Olympic and Paralympic medals, thus curling is “a flagship” sport for Scotland. Given the importance of the sport it is somewhat surprising that our study was the first to apply circular statistics to the analysis of curling data. As the results revealed, the analysis of the behavioural data provides valuable insight into differences within and between athletes in how the stone delivery was distributed around the house. Our analysis suggested that most of the athletes exhibited consistent and homogenous stone location distribution within their stone delivery. However, one participant’s stone delivery varied substantially from block to block, with no consistent pattern within their stone delivery. The information provided by the diagrams and figures produced with the use of circular statistics can clearly help coaches and sport practitioners design interventions suitable for each athlete that will help guide and improve their stone delivery performance (e.g., designing practice routines to correct a right- or left-sided bias). Equally, from a sports practice perspective, longitudinal assessment of individual profiles of stone delivery would provide a strong basis for informing talent selection (e.g., selecting more consistent curlers) and tactical selection of athletes within competitions (e.g., in response to the need for a left- or right-sided bias). Based on the present findings, therefore, we strongly recommend that coaches and sports practitioners should adopt our behavioural analysis approach as a method for monitoring and assessing curling performance in each athlete.

The main aim of this study was to investigate the feasibility of recording EEG data within a curling context. The procedural routine of the task adopted for the purposes of this study was ideal for EEG data collection because repetitive trials were performed and there was limited movement required to release the stone (sliding down the ice). Based on the timing information collected during performance we established a baseline period that should have been relatively uncontaminated by processes engaged during the pre-shot period. Importantly, our assessment of the RMS data confirms that there were no reliable differences present during the baseline period. In short, our data quality check suggests that EEG data recording is viable during curling. The current findings therefore add to our previous results in demonstrating that EEG can be used effectively in a range of real sporting contexts, building confidence in the mobile EEG approach for both researchers and sports practitioners alike.

As we highlighted in the introduction, Arns *et al.,* (2008) has argued that researchers in the sporting domain need to adopt a personalized approach, not just by understanding the profile of individual athletes, but also by investigating neural activity within the context of different sports. It is important for coaches, sports practitioners, and researchers to understand each sport individually, as the variable nature of the task demands associated with each sport means that there are likely to be differences in the underlying neural activity characterizing successful performance from sport to sport. In broad terms, therefore, and in line with Arns *et al., (2008)* suggestion, the current data reveal a quite different pattern of EEG effects than was reported in relation to successful shooting. Although shooting and curling are both target sports, the pattern of EEG findings varies considerably across these two sports. It will therefore be important for future studies to investigate if it shares neural characteristics underlying successful performance with other target sports such as archery, golf, etc. We return to this issue in more detail in the general discussion, in relation to psychological models of sporting expertise. Here, by contrast, we focus on the specific pattern of EEG findings reported in the current experiment.

Averaged across 7 elite curlers, we identified a change in alpha power in the period just before the curlers released the stone (i.e., from -600ms to -300ms) over central parietal scalp (electrode CP5). More specifically, there was significantly more alpha power (8-12Hz, including changes in both low and high alpha), underlying successful compared to unsuccessful performance. Based on previous analyses of curling, and wider evidence from EEG studies, we suggest that the changes in alpha most likely reflect processing associated with the control of balance. Balance control usually depends on integrating information from vestibular, somatosensory, and visual systems, which provide a link between the neural network for controlling the neck, hip, and ankle joints (Allum & Honegger, 1992). According to Horak *et al.,* (1996) if the information provided by the vestibular, somatosensory, or visual system is inaccurate, then balancing becomes unstable. Moreover, previous research suggests that a key function of the centro-parietal and parietal lobes is somatosensory processing (Bastos et al., 2020). Within our study balance control would be expected to vary with successful performance, as previous (behavioural) evidence suggests that the most critical component for successful performance in curling is postural stability during the sliding phase and releasing of the stone.

According to Hulsdunker *et al.,* (2015b) when there is an increase in postural demands, alpha power reduces in the centro-parietal region. Conversely, evidence has suggested that greater instability is associated with decrease in alpha power over centro-parietal regions. Support for this view of alpha comes from a study by Del Percio et al., (2009). EEG and stabilogram data were collected simultaneously in elite karate and fencing athletes, and in non-athletes, during an upright standing condition of eyes open and eyes closed. The researchers were interested in examining the correlation between cortical activity and body sway when visual inputs were available during the balance control task. Higher alpha amplitude was found in karate and fencing athletes compared to non-athletes at centro-parietal electrodes. Moreover, the higher the alpha amplitude the better the balance of the athletes, leading the researchers to suggest that the increases in alpha power might lead to the integration of intra- and extra-personal space arising from the somatosensory and visual systems. Similarly, Fasold *et al.,* (2002) have suggested that the key functional role of the centro-parietal region is the integration of visual, somatosensory, and vestibular information. In line with the suggestion provided by Del Percio et al., (2009), our results suggest that to perform successfully curlers must integrate spatial information representing themselves in the dynamic environment of curling, allowing them to orient correctly as they move along the ice, prior to release of the stone.

Additionally, we identified that only for high alpha power (10-12Hz), in the period prior to the releasing of the stone (-500ms to 0), there was a significant increase in activity underlying successful compared to unsuccessful performance over central scalp (specifically at electrode C4). According to previous research the right-central region (underlying C4) is associated with motor control of the left arm/hand (Yi et al., 2016). From this perspective the pattern of results reported in the present study suggests that successful performance is associated with inhibition of the left arm/hand, reflecting the need to inhibit a learnt motor response. More specifically, our curlers place their left hand by their side whilst holding the brush, using the left hand/arm as a balancing aid during the delivery of the stone. From this perspective the pattern of results exhibited here suggests that successful performance is associated with fine motor control, characterized by inhibiting the left hand used for better postural stability the closer the athletes get to the target and release of the stone.

The present data also provide evidence that changes in the alpha frequency were temporally and topographically distinct from changes in the theta frequency. Whilst difference in alpha were present at left centro-parietal (CP5/-600ms to -300ms) and right central (C4/-500ms to 0) electrodes, changes in theta (4-7Hz) power were present over right frontal-central scale (F4/FC6) and statistically reliable across the whole two second time period. According to previous research in the wider neuroscience domain it has been proposed that increases of fronto-central theta power reflect the operation of a postural error detection system which monitors postural stability/instability and commences postural responses in order to adapt in situations of high postural instability to either maintain or regain balance (Sipp *et al.,* 2013; Hulsdunker *et al.,* 2015a). Additionally, it has been suggested that increases in theta at frontal and fronto-central regions are indicative of increased attentional demands during a balance control task (Sipp et al., 2013). Consistent with this view, in the context of our curling task, the results would suggest that during the delivery of the stone theta increases reflect the maintenance and monitoring of postural stability, leading to better balancing and resulting in a greater likelihood of achieving a successful performance. Additionally, the increases in theta activity underlying successful performance are consistent with an increase of attentional processing that is responsible for better balance, a necessary precursor for successful performance.

In conclusion, this was the first study to investigate cortical activity during a real-world curling task. Our results exhibit that it is feasible to collect and analyse EEG data during a real-world curling task. Additionally, significant differences in alpha and theta power have been identified, for successful compared to unsuccessful performance. A comprehensive integrative view of our results suggests that increases in alpha and theta power during a real-world curling stone delivery most likely reflects an increase of attentional processing (theta) and/or the maintenance and monitoring of balance stability (theta), alongside an increase in the integration of sensory and spatial information regarding one's own body, stone and visual target (alpha), processes which together lead to successful performance. The present results are necessarily speculative, of course, because this is the first study investigating cortical activity as a function of performance in curling. One implication of our functional interpretation of the EEG findings is that it suggests future studies should focus on measuring postural balance and the relationship between cortical activity and postural balance within a real-world curling task.

Finally, it is important to acknowledge that from the perspective of sports practitioners a key limitation of the current study is the adoption of a group average approach to the analysis of the EEG data. Although focusing on group average data provides a powerful method for identifying commonalities across individuals, sport practitioners are ultimately interested in understanding neural activity as a function of performance at an individual level. That is, whilst EEG methods used within the wider sports domain (and in Chapter 3 of this this PhD) typically rely on examining group averaged data, for sports professionals' the primary goal is to gain understanding into the processes supporting individual performance. In response to this requirement Chapter 4 of this PhD focused on examining the individual EEG profiles characterizing successful versus unsuccessful performance within two elite Air-Rifle athletes, revealing clear differences in the patterns of neural activity exhibited by each athlete. Chapter 4's focus on individual EEG profiles demonstrated that the cognitive and neural processes supporting successful performance can vary across individuals. Importantly, however, questions remain as to whether neural activity associated with successful performance is consistent within each individual over time - across sessions or blocks of performance. From this perspective, we suggest future studies examine neuronal activity underlying successful versus unsuccessful performance over sessions, and identifying differences or similarities within one expert athlete, will bring us one step closer to a truly individualized approach.

Chapter 6: General Discussion

6.1 Summary of findings

The studies reported in Chapters 3, 4 & 5 of this thesis demonstrate that by working in collaboration with sporting professionals, athletes and coaches, sporting performance can be successfully examined using mobile EEG, across various sporting tasks (pistol shooting, Air-Rifle shooting and curling), in ecologically valid settings. The prior sports EEG literature suffered in terms of ecological validity, with studies employing entirely non-sporting tasks such as button presses (Di Russso *et al.,* 2005). A critical review of this literature was presented In Chapter 1 (Introduction), highlighting the lack of ecological validity in EEG research investigating sporting performance. The limitations were discussed, along with suggestions about how greater ecological validity could be achieved and how the findings could be more informative for sports practitioners. From the perspective of sports practitioners, employing tasks that are not representative of real-world sporting tasks not only sacrifices the ecological validity of the tasks but also minimises the potential impact of the findings by reducing their applicability in real world settings.

Through our literature review we identified that most studies investigating neural activity underpinning sporting success have employed between subjects designs that compared experts to novices (Hatfield *et al.,* 1984; Babiloni *et al.,* 2010). These findings have highlighted differences in the neural mechanisms between experts and novices in various sports. Although we do not question their valuable contribution in revealing changes in cognitive and neural processes related to the development of expertise, it is important to point out that their findings may also reflect pre-existing differences between individuals that allow one to become an expert. More importantly, such studies do not necessarily provide information about the mechanisms that underlie successful and unsuccessful performance within experts, which is the primary focus of interest within the sporting domain.

A summary of the findings of the studies employed in this PhD is presented below, prior to further discussing the findings further.

Sport	Frequency	Time	Location	Pattern of activity for levels of performance	Psychological Interpretation
Pistol (Ch.3)	Alpha (8-12Hz)	-1000ms to 0	P3/Pz/P4	Increase of alpha activity for both levels, with higher increase underlying unsuccessful performance	Increase of alpha was observed prior to both levels of performance, with more increase underlying unsuccessful performance suggesting that a lesser cortical activation was present for unsuccessful The pattern of results would suggest that athletes are able to successfully perform without being in a fully automatic stage characterized by lesser cortical activation (Comani et al.,2014).
	Theta (4-7Hz)	-500ms to 0	F3/Fz/F4	Increase of theta activity for both levels, with higher increase underlying unsuccessful performance	Increase of theta was observed prior to both levels of performance, with more increase underlying unsuccessful performance suggesting that higher amount of excessive attentional engagement might damage the successful execution of performance (Kao et al., 2013).
	SMR (13-15Hz)	-1000ms to 0	C3	Increase of SMR activity for both levels, with higher increase underlying unsuccessful performance	Increase of SMR was observed prior to both levels of performance, with more increase underlying unsuccessful performance suggesting that better movement planning supported successful performance (Cooke et al., 2014).
	Beta (15-30Hz)	-1000ms to 0	C3/C4	Increase of beta activity for both levels, with higher increase underlying unsuccessful performance	Increase of beta was observed prior to both levels of performance, with more increase underlying unsuccessful performance suggesting that better movement planning supported successful performance (Cooke et al., 2013).
Air-Rifle (Ch.4)					
Participant 1	High Alpha (9-13Hz)	-3000ms to -1000ms	FC1/Cz/FC2	More alpha activity for successful	The pattern of result is indicative of lower cortical activation associated with movement automaticity (Comani et al., 2014).

Participant 2	Theta (4-7Hz)	-3000ms to -2000ms	FC1/Cz/FC2	More theta activity for successful	The athlete was able to allocate cortical resources and focus their attention to the moment of the shot (Doppelmayr et al., 2008).
Curling (Ch.5)					
	Alpha (8-12Hz)	-600ms to -300ms	CP5	Increase of alpha activity for both levels, with higher increase underlying successful performance	Successful performance was associated with an integration of dynamic changes in spatial information and better orientation of themselves in the curling environment (Yi et al., 2016).
	High Alpha (10-12 Hz)	-500ms to 0	C4	Increase of alpha activity for successful	Successful performance was associated with highly practiced and well learnt motor processes, performed in an automatic way and without excessive thinking (Comani et al., 2014).
	Theta (4-7Hz)	-200ms to 0	FC2/FC6	More theta activity for successful	The pattern of results suggests an ability of allocating cortical resources and focusing of attention to the to detect and correct any postural istability that would have been detrimental to performance (Doppelmayr et al., 2008; Shank et al., 2012; Sipp et al., 2013)

Table 6.1. Overview of EEG changes across all studies forming this PhD and their psychological interpretations.

Neural Mechanisms supporting Pistol Shooting Performance

In the first study (Chapter 3) exploring the neural activity underlying successful/unsuccessful performance within a group of expert Pistol shooters, we demonstrated that the pattern of effects reported in studies comparing experts versus novices are not similar to those that are seen when comparing successful and unsuccessful performance within experts. Previous studies have reported alpha (10-12Hz) *increases* over left-temporal (Haufler, Spalding, Santa-Maria & Hatfield, 2000) and parietal-occipital (Babiloni *et al.,* 2010) areas for experts compared to novices. In our study we identified that in the period just prior to the trigger pull (-1000ms to 0ms) there was a larger increase for unsuccessful performance at parietal electrodes. A similar pattern of results has been reported in golf putting by Babiloni *et al.* (2008), visible in the period preceding successful putts, and present over Fz, Cz and C4 electrodes. Taken together, these findings provide strong support for the view that comparisons between experts and novices cannot be used to infer how experts achieve successful performance.

In line with previous research in the sporting domain, Comani et al., (2014) had reported increases in the alpha band underlying successful controlled performance suggesting that athletes can reach successful performance levels without being in a fully automatic state as reflected by the lesser increase for alpha underlying successful performance. Thus, in functional terms, our findings provide support for the idea that, during shooting, the lower levels in alpha power that precedes successful performance reflects the athlete’s ability to reach successful performance without the need of being in a fully automatic state. Changes in alpha did not occur in isolation however. Changes in theta activity were also observable, and statistically significant, at frontal electrodes during the last 500ms before the trigger pull. Although previous research has reported *increases* in frontal midline theta, for experts compared to novice shooters (Doppelmayr, Finkenzeller & Sauseng, 2008), our results are in line with previous Kao et al.., (2013) research indicating that a *lower increases* in theta activity was present for successful compared to unsuccessful shots within experts. As with changes in alpha power, therefore, the changes in theta power that have been observed between experts and novices simply are not always seen when successful and unsuccessful performance is examined within experts.

Whilst our findings for theta differ from those reported between expert and novice shooters, they are in line with those of Cooke *et al.* (2014) and Kao et al., (2013), who compared EEG neural activity between experts and novices during a golf putting task. The researchers reported lesser theta in experts in the period preceding the putt, which was interpreted as reflecting the expert's greater ability to control their attention. From this perspective, in functional terms, the increase of theta that we observed for unsuccessful performance during the last 500ms prior to the trigger pull most likely reflects disturbances in information processing - a failure of top-down attentional focus which results in a detriment to performance (Chuang *et al.,* 2013; Bakhshayesh *et al.,* 2011). Additionally, Kao et al., (2013) reported a lower frontal midline theta activity characterizing successful performance suggesting that higher amount of excessive attentional engagement towards the task might lead to detrimental consequences for performance. This functional interpretation of the current findings makes sense in cognitive terms, mapping onto the athletes and coaches view that focusing and maintaining attention is critical for successful performance. From an experimental perspective, however, the findings suggest an important direction for future studies is to directly manipulate attention, for example via training using video games or computer exercises (Posner et al., 2015) or using interventions such as mindfulness (Semple, 2010).

The findings from Chapter 3 also highlighted that the existing literature has been overly focused on changes in alpha and theta. Rather than focusing on these two power bands, we examined a broad spectrum of activity, which allowed us to also reveal more increase in beta and SMR power in unsuccessful compared to successful performance. The SMR effect was found over the left central region (C3 electrode), whereas beta was present bilaterally at electrodes over the central motor region. Although changes in beta and SMR have not been widely reported, the findings are in line with previous research, linking beta and SMR to motor processing (Cooke *et al.*, 2014). The results suggest that compared to unsuccessful performance, the reduction in SMR and beta power might reflect better movement planning underlying successful performance.

More importantly perhaps, overall, the findings from Chapter 3 suggest that there is a similar pattern of neural activity underlying unsuccessful and successful performance across a range of frequency bands (parietal alpha, frontal theta, central beta and SMR) leading to an understanding that each frequency is a critical component for the successful execution of the task. Overall, each band has been reported to exhibit a lesser increase in activity during the last second prior to the trigger pull underlying successful performance - a finding that could not have been predicted based on the differences reported between experts and novices.

The findings revealed in Chapter 3 also provided new insight into the methods used to investigate performance. Traditional approaches have examined 3 second epochs of activity during the pre-shot period. The present findings demonstrate that employing a 3 second epoch (the dominant approach in the literature) did not allow any statistically reliable effects to be established. Indeed, based on visual inspection of the time frequency plots we identified that the EEG effects present within our study largely reflected short-lived bursts of activity. This led us to gradually refine our approach to analysing the data, examining and targeting smaller 500ms time windows to capture the changes in neural activity across frequency bands. Consequently, a finer grained approach to analysis of the time frequency plots was adopted in Chapters 4 and 5. Based on the experiments reported here we conclude that future studies should adopt a tailored approach, guided by visual examination of the data - allowing the dynamic nature of the processing to be revealed.

As noted above, it is also important to highlight that the findings from Chapter 3 do not just advance scientific understanding. We believe that the findings revealed in Chapter 3 are also of great importance to sports professionals. For example, the lesser decrease in parietal alpha underlying successful performance suggests that the athletes are using their cognitive resources to support a spatially attentive state, focusing on key visuo-spatial information without fully being in an automatic state (Comani et al., 2014). It is unclear, however, which features of the environment are most important, or whether some aspects of the environment actively interfere with the athletes' attempts to focus. From an applied perspective shooters and coaches might benefit by developing and implementing training protocols that seek to improve the shooters' ability to directly focus on key visuo-spatial information which is available to them from the visual target. Furthermore, by implication, the present findings suggest that future studies should seek to characterise the perceptual demands of each sport, identifying exactly where and when attentional focus is required.

The primary focus of interest in Chapter 3 was the investigation of neural activity. However, we also examined the behavioural performance of our participants, identifying that, on an individual level, there was considerable variability in the mean and range of shooting scores. At the same time, our review of the wider EEG literature made it clear that the frequency band associated with changes in alpha activity might vary across individuals (Angelakis *et al.,* 2014), suggesting that the pattern of alpha revealed in the average EEG data may not have applied to all of the athletes equally. This consideration led to a critical question regarding the similarity of EEG and behavioural profiles characterizing successful performance across expert athletes. From a sports perspective, coaches and professionals are interested in understanding patterns of neural activity associated with successful and unsuccessful performance at an individual level, providing strong motivation for investigating neural activity associated with different levels of performance at an individual level.

''New statistics'', Individualistic Approach and the Neural Efficiency Hypothesis

Consequently, Chapter 4 focused on examining individual variability at a behavioural and neuronal level, investigated kinematic and EEG data during Air-Rifle shooting to provide a more detailed view of the individual differences in sporting performance across athletes. Rather than examining a traditional group average, we examined two expert shooters, adopting an N=1 approach. It is acknowledged that in specific areas of research (including elite sports), we might need to work with very small sample studies. N-of-1 single subject studies are of particular interest in medical studies. The ultimate aim of N-of-1 studies within the medical field is to determine the best intervention for individual patients by using objective data-driven criteria (Lillie *et al.,* 2011). Single patient studies are important in health psychology too, as they can be useful to provide more precise treatments for individual patients (Shaffer *et al.,* 2018). Single subject studies have recently regained interest and are regarded as an important aspect of research resulting in producing outcomes which suit single patients or participants (Shaffer *et al.,* 2018). When studying elite athletes (an expert and limited population) researchers necessarily have to rely on small sample sizes. Throughout Chapter 4 we had to overcome the issue of examining our data through group averages as we were interested in investigating neural power in successful/unsuccessful performance within each individual, resulting in a more individually tailored approach. However, the approaches used in previous neuropsychology or sporting literature would not have provided a solution to our approach (see Chapter 4, section 4.3).

Previous literature in the sporting domain has used visual inspection of frequency scalp maps to characterise differences across levels of performance. However, that meant abandoning traditional statistical testing and relying instead on interpretations driven by visual inspection of the data. Given the growing concerns about the Null Hypothesis Testing Approach, examination of the literature led us to the understanding that alongside the visual inspection of the data, descriptive statistics can be used to provide a more quantifiable assessment of the data, as suggested by Cumming & Calin-Jageman (2017) in their ‘new statistics’ approach. Thus, in Chapter 4 we employed the new statistics approach, using descriptive statistics to characterise the pattern of results based on the means and 95% confidence intervals associated with the data. Although the approach used in Chapter 4 was novel within the context of sports EEG, according to the new statistics literature it should have provided us with a robust basis to interpret the pattern of results. Having used this approach the findings led to a clear understanding that considerable amounts of data are required for each individual athlete if the new statistics approach is to be worthwhile. Overall, the findings from Chapter 4 provide support for adopting an N of 1 approach in future studies, especially if researchers are interested in understanding individual differences in the neural mechanisms underlying successful/unsuccessful performance within elite athletes.

The individualistic approach acquired in Chapter 4 led to a key methodological development; the adoption of tailored definitions of the EEG frequency bands - using an eyes-open-eyes-closed pre-screening procedure to define the Individual Alpha Peak Frequency (IAPF) in each shooter. Whilst adopting an IAPF approach led to no change in the definition of the frequency bands for one of the shooters, for the other shooter the IAPF approach altered the definition of alpha from 8-12Hz to 9-13Hz - a change that also required adjustment to the definition of theta. Thus, a critical finding from Chapter 4 was that the traditional frequency band definitions do not fit all athletes, and a group average approach therefore carries a strong risk of mischaracterizing the pattern of neural activity for some individuals. In broad terms, therefore, the findings from Chapter 4 demonstrate that adopting an individualistic approach and calculating the Individual Alpha Peak Frequency can result in differences in how we define alpha, and neighbouring frequencies, and thus how we interpret our pattern of results.

As well as changing the definition of alpha, tailoring the analysis revealed a somewhat different pattern of effects. More specifically, for Participant 1, a relative change was found for successful compared to unsuccessful performance in the *a-priori* defined alpha power (8-12Hz) at fronto-central electrodes. Whereas low alpha power (8-10Hz) was greater for unsuccessful performance, greater high alpha power (10-12Hz) was evident for successful performance. However, when shooting performance was investigated using an IAPF approach, we observed similar levels of alpha power (9-11Hz) amplitudes in successful and unsuccessful performance, whereas there was an evident increase in high alpha power (11-13Hz) in successful compared to unsuccessful performance at fronto-central electrodes.

The changing pattern of effects clearly demonstrates the importance of calculating IAPFs, especially when examining performance differences with regard to alpha power (Haagens *et al.,* 2014). More importantly, in terms of theory, the findings revealed by the IAPF analysis are difficult to reconcile with the neural efficiency hypothesis (Del Percio *et al.*, 2009a, see Chapter 4). As outlined in Chapter 1 (see section 1.4.1) the neural efficiency hypothesis states that cortical activity is reduced in expert athletes after prolonged periods of training, leading to expert athletes requiring less cortical activation (reflected by an increase in alpha power) compared to novices (Del Percio *et al.,* 2009a), consistent with the skill acquisition model provided by Fitts and Posner (1967). It is notable, however, that these theoretical accounts were developed in studies comparing experts versus novices, describing three progressive stages of learning and expertise (from effortful conscious processing, through improved proficiency, to fully automatic execution). The findings from Participants 1 and 2 presented in Chapter 4 are difficult to reconcile with the neural efficiency hypothesis because successful performance was associated with quite different patterns of activity in each athlete, presumably reflecting different strategies in each case. Taken together, therefore, the distinct pattern of effects seen in each participant not only suggests that a group average approach cannot fully explain expert performance, but also suggests that a single theoretical account cannot capture the variability that exists between athletes Put simply, the findings of this study reveal quite different EEG profiles across the two shooters, suggesting that different mechanisms are activated and engaged in each individual athlete, which no existing theoretical accounts of sporting expertise can accommodate.

To our knowledge, Chapter 4 was the first to explore differences between *a-priori* and IAPF measures of alpha power in individual athletes. The data provide a strong basis for arguing that future studies in the sporting domain should adopt and assess IAPFs in each individual, even if a group average approach is employed. The assessment of the Individual Alpha Peak Frequency via a comparison between eyes-open and eyes-closed states is not an onerous process and the benefits of this approach clearly outweighs the time costs of additional data collection. Unfortunately, although we now believe that IAPFs should be used routinely, it is notable that we did not do so in Chapter 5 for our curling athletes, as the curling data was collected in line with the schedules and availability of our athletes and prior to us fully examining the outcomes of Chapter 4. Nonetheless, having fully understood the importance of the IAPF approach it is clear that the findings from any study that uses traditional frequency bands must be interpreted with caution.

The importance of an individualised and tailored approach to the assessment of sporting expertise is reinforced by consideration of the behavioural data. In the studies reported in Chapters 3, 4 & 5 we collaborated with athletes and coaches to develop tasks that would be representative of the athletes training and would not interfere with the athlete’s practice routines. One important feature of this strategy is that throughout these studies we were able to define successful performance in a manner that was most meaningful to the athletes. For example, in shooting we defined successful performance based on the mean of all shots fired. However, in Chapter 4 (4.6 Results: Shooting Behavioural Performance) we were also able to examine behaviour in more detail, based on six indicators provided by “SCATT” - kinematic measures taken from the Air-Rifle during the preparation period.

We examined the relationship between performance for each participant and the SCATT indicators using a Pearson (two-tailed) correlational analysis. As with the EEG data, analysis of the SCATT data revealed different patterns associated with successful performance for each athlete, highlighting the need to adopt an individualistic approach to examine the kinematic data. Our findings show that although a group of athletes might be considered homogenous in terms of their level of expertise (as per the two elite Air-Rifle athletes), the way in which that expertise is achieved can clearly differ between the athletes. Put simply, these data suggest that an individualised approach should be adopted even when examining behavioural performance. In practice, of course, it remains the case that the vast majority of studies in the sporting domain examine performance across an average of all participants (Araujo & Davids, 2016). However, our findings suggest that examining performance through group averaging might not be appropriate even in groups of experts, arguing instead for the adoption of an ”individualised, process-oriented approach’’ (Araujo & Davids, 2016, p.3).

The drive towards an individualised approach is further supported through consideration of the behavioural data in Chapter 5. To explore curling performance, our study was the first to apply circular statistics. The results revealed differences within and between athletes based on the pattern of their stone delivery and the stone distribution around the house. The findings revealed that most of our athletes exhibited a consistent and homogenous stone location distribution within their performance. By contrast, however, one participant’s stone (P7) delivery varied from block to block, and no consistency was exhibited within their stone delivery. Circular data can be used to characterise how consistent behavioural performance is. The knowledge and understanding of circular data is limited in the wider research domain (Cremers & Klugkist, 2018). However, there is a need to understand that circular data behave differently from linear data. Thus, by using circular statistics we can represented the data on circles, by using measurements of 0° and 360° that reflect the same direction compared to a linear scale where 0 and 360 are located in opposing ends. Additionally, circular statistics provide a measure of consistency and can be used to quantify behavioural performance. Clearly, the circular statistics are useful for characterising the pattern of behaviour in each athlete, for example to identify talent, or to assess whether training interventions are successful. Regardless, based on the present findings, we highly recommend that coaches adopt behavioural analysis, including the use of circular statistics, as a method for monitoring and assessing performance in target sports (i.e., sports in which circular statistics can be readily applied such as golf, shooting and archery).

Issues arising from pre-determined baseline periods

The investigation of behavioural shooting performance, through the SCATT system, provided the opportunity to examine the choices that have been made around baseline normalization - an issue that is rarely reported in the sporting literature. As noted in Chapter 3, concerns have been raised about the methodology employed in the sporting EEG literature, in particular the choice of baseline period (if stated) (see Table 3.1). In Chapter 3, we followed the most common practice of baseline normalization to investigate changes in neural activity underlying successful and unsuccessful performance. However, in Chapter 4, we identified that the appropriate baseline period was likely to vary across individuals. In stark contrast to the previous literature (which largely used a predefined baseline period of -5000ms to -4000ms), the kinematic data provided by the SCATT system suggests that elite shooters are highly variable in the timing of shot engagement. More importantly, a baseline of -5000ms to -4000ms is not appropriate because the SCATT data suggests the shooters are actively engaged in preparing for their shot engagement during this period. Equally, however, the time taken from picking up the Air-Rifle to taking the shot also varied from individual to individual, suggesting that a single pre-defined period would not provide an equivalent baseline across individuals. Given this behavioural pattern the only way to achieve appropriate baseline periods appears to be via the identification and tailoring of individual baseline periods (such that they do not involve active preparation regarding the task of interest). Consequently, in line with the findings in Chapter 4, we established a baseline period for Chapter 5 by examining behaviour and established a period, which to the best of our knowledge, did not contain any cognitive processing directly linked to the stone delivery phase.

Our conclusions about the problems associated with the baseline period clearly pose a critical question for the results reported in Chapter 3. As mentioned above, in Chapter 3 we employed the common baseline approach used within the sporting domain. Subsequently, however, based on the findings in Chapter 4, we identified that assessing and tailoring the baseline period with the use of kinematic data is critical. It would therefore have been beneficial to re-assess the findings from Chapter 3, generating a tailored baseline period for each individual and investigating how changes in the baseline period affected the interpretation of the data. Unfortunately, due to technical issues we were not able to collect kinematic data using the SCATT software for our pistol-shooting cohort. Nevertheless, future studies should take our findings from Chapter 4 into account - the present data strongly suggest that all studies should collect and analyse kinematic data to calculate individualized baseline periods for each shooter, providing a more suitable baseline period.

Overall, as the preceding discussions make clear, the findings from Chapter 4 led to the rejection of a “simplistic’’ one-size-fits all approach to understanding sports performance. In particular, our data suggested that the traditional group average based approach that has been widely adopted within the sporting domain cannot account for the variability which exists across participants at a neuronal and behavioural level (Arns *et al.,* 2008). As noted above, however, Arns *et al.,* (2008) has also argued that sporting research must examine task-related ecologically valid training in the context of various sports. Consequently, having examined shooting in detail, we turned to an examination of curling. The crucial question was whether equivalent insights into the processes underlying expertise could be gained by examining the neural activity characterizing successful and unsuccessful performance in a curling task. In line with Cooke’s (2012) suggestion, we expected that different patterns of EEG activity might be present across preparation stages of different sports.

Curling and EEG

Thus, Chapter 5 focused on examining EEG data during a curling task within a group of expert athletes. To our knowledge, the study presented in Chapter 5 is the first one to examine neural activity underlying successful versus unsuccessful curling performance in an ecological valid setting. As outlined in Chapter 5, the findings revealed increases in alpha over left centro-parietal electrodes. Overall, from a functional perspective, the findings are consistent with the view that curlers must be able to integrate dynamic changes in spatial information, orientating themselves in the environment as they release the stone. The data suggest that successful performance is associated with the kind of fine motor control that is characterized by inhibition, and that the kind of highly practiced and well-learnt motor processes involved in sporting behaviour must be performed automatically and without excessive thinking - as reflected in the higher increase of alpha underlying successful performance (Yi *et al.,* 2016).

In addition to changes in alpha, successful curling was also associated with changes in theta. More theta activity increases were seen at right frontal-central electrodes and were evident across the entire two second time period leading up to the stone release. This finding is particularly interesting from a functional perspective, as it suggests that during the stone delivery curlers must maintain and monitor their postural stability (as reflected by the increase in theta), consistent with the view that postural control is an important aspect of successful curling performance (Shank *et al.,* 2012). To be effective curlers must detect and correct any postural instability - leading to better balance and resulting in successful performance (Sipp *et al.,* 2013). Rather unexpectedly, the fact that theta increase was recorded at right central electrodes suggests that control of the non-dominant left hand (which does not release the stone) may be particularly important. This finding also provides a clear target for future studies. For example sports practitioners may be able to enhance performance by training curlers in postural stability - particularly the ability to inhibit unnecessary movement. Similarly, future EEG studies should measure postural stability during the preparation period to examine the relationship between theta and postural stability. Put simply, the present findings suggest that future studies of curling should employ additional measures to monitor postural stability and changes in the various frequency bands.

It is also important to acknowledge that our study of curling illustrates one of the benefits of focusing on group average data - this approach provides a powerful method for identifying commonalities across individuals. Because no one had previously attempted to assess and examine neural activity within a curling task, the group average approach was a sensible starting point. Nonetheless, as stated throughout this thesis, our view is that this first exploratory study of EEG in a real-world curling task simply provides the basis for further studies to move beyond group level analyses. Future studies should examine neuronal activity underlying successful versus unsuccessful performance within individual curlers, examining variability over time (over multiple curling sessions, or as a function of experience), and identifying differences or similarities between experts, bringing us one step closer to a truly individualized approach.

Methodological challenges covered in this PhD

Finally, we highlight one further methodological issue raised across the thesis. As should hopefully be clear by this point, the studies employed in this PhD successfully demonstrate the feasibility of recording EEG data within real-world sporting settings. Within all of our studies a 32-electrode montage (based on the International 10-20 system, Jasper, 1958) was used to acquire EEG data. The present findings demonstrate that employing a broad coverage of the scalp is important, because the EEG effects were present in variable locations across the scalp. Previous studies in the sporting domain have typically focused on a small number of specific predetermined electrode locations, meaning that only a subset of the EEG effects could be revealed. Our data reveals that a broader coverage of the scalp leads to a more comprehensive and holistic view of the processes underlying sporting performance. The importance of sampling broadly across the scalp also clearly interacts with the importance of examining various frequency bands, rather than focussing on just a single band such as alpha. Indeed, our approach of simultaneously examining multiple frequency bands was dependent on the use of a global head montage, revealing power modulations in distinct frequency bands at different locations across the head. A significant challenge for future studies will be to investigate the interactions between the different effects, characterising how the different processes work together to support successful sporting behaviour.

6.2 Concluding remarks

We have demonstrated that mobile EEG can be used for the assessment of real sporting behaviour. Our studies add to the existing literature by increasing the understanding of the psychophysiology of action preparation (see Table 6.1 for an overview of the EEG changes across studies). One clear outcome from the current work is that investigating differences in neural activity between experts and novices is not sufficient for understanding elite performance. By moving from the examination of group averages to a focus on individuals we have demonstrated that a highly tailored approach is not only possible but could be considered essential for researchers and practitioners hoping to increase understanding of the cognitive and neural processes supporting sporting behaviour.

As a high-level summary of our results, we have illustrated the complex multifaceted nature of the pattern of cognitive processes underlying successful performance across various sports. In particular, this PhD highlights that there is considerable variability in the frequency bands involved, in the timing of the effects, in the location of the effects, and in the specific pattern of activity associated with success across the sports assessed in this PhD. In broader terms, the findings are in line with Cooke's (2012) suggestion that different patterns of EEG activity might be present across preparation stages of different sports. Importantly, however, there are also similarities across the studies. For example, the central region (electrodes overlying motor cortex) seems always to be implicated - consistent with the fact that in each sport activity is being examined during a preparation stage, prior to the initiation of movement. The pervasiveness of motor related activity should not come as a surprise given that precise controlled movements are an inherent component of sporting actions (trigger pull/sliding etc). Nonetheless, the results also reveal that there are differences in the timing of motor related EEG changes, highlighting the importance of assessing and examining the pattern of effects across various sports.

The studies presented here also highlight the necessity of gaining insight into the processes supporting individual athletes. Throughout our studies there was evidence of variability across athletes. Traditionally, the use of EEG methods within the sporting literature has relied on examining group average data, but our data provide evidence of behavioural variability between and within athletes. Although studies comparing experts and novices are insightful, they are unable to fully address the question of how elite athletes achieve high levels of performance and what differentiates successful and unsuccessful performance at the highest level. Given our findings, we propose that future studies should follow a more individualised approach reflecting each individual athlete’s behavioural profile. Note, however, that we are not suggesting that examining and understanding cortical activity in groups should be entirely abandoned. Instead, we believe that a combination of group and individual approaches should lead to more insightful data. In particular, we propose that future studies should always employ detailed behavioral measures (such as kinematic data) that can be used to inform a tailored approach - including defining appropriate baseline periods and periods of interest for analysis, structured to fit an individual’s behavioural profile.

Overall, we conclude that future studies would benefit from adopting our multi-measure approach to studying preparation for action in sports. This thesis has demonstrated the feasibility of capturing neural data in real world sporting settings across various sports. In doing so, we have examined neural activity underlying different levels of performance across a cohort of athletes, as well as investigating and comparing individual athletes. The findings provide clear evidence that the cognitive and neural processes underlying sporting behaviours can be studied, demonstrating that a ‘’simplistic’’ one-size-fits-all approach does not lead to a comprehensive understanding of superior elite performance and that a full understanding requires an individualistic approach to be employed.

Appendix A

Chapter 4- Follow up Correlational Analysis

A.1. Correlational Analysis (Participant 1)

Correlational analysis were performed on all single trials, focusing on -3000ms to -1000ms time window for fronto-central (FC1/FC2/Cz) high individual alpha (11-13Hz) in line with the significant results exhibited from the ANOVA. No significant correlation was found between fronto-central high alpha power and performance (r (254)=.11, p =0.07).

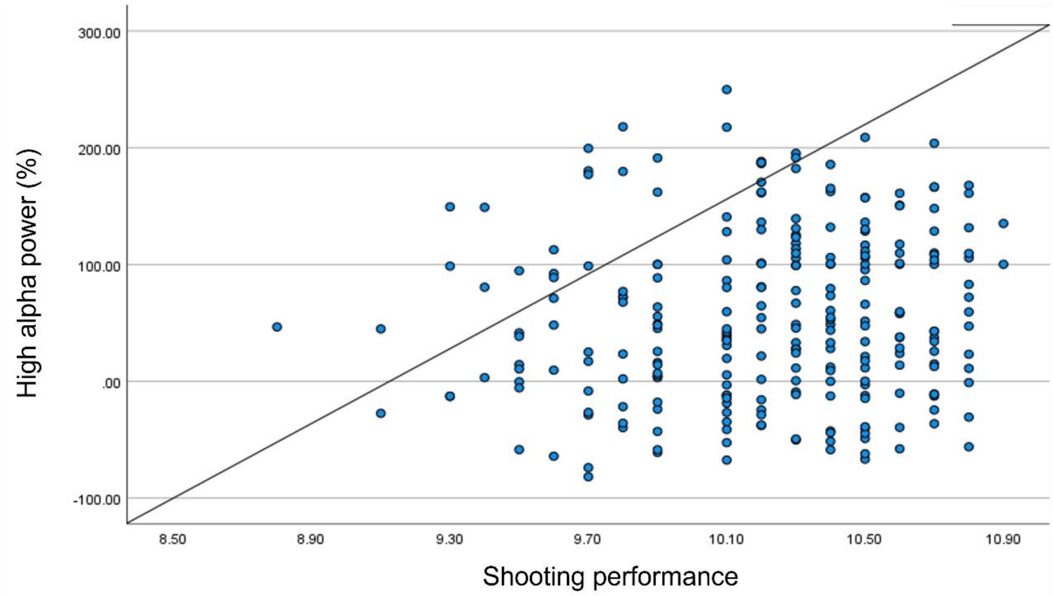


Figure A.1. Relationship between performance and alpha (11-13Hz) activity at fronto-central area during -3000ms to -1000ms.

A.2. Correlational Analysis (Participant 2)

Correlational analysis were performed on all single trials, focusing on -3000ms to -2000ms time window for frontal (F3/Fz/F4) theta (4-7Hz) in line with the significant results exhibited from the ANOVA. No significant correlation was found between frontal theta power and performance (r (184)=.12, p =0.10).

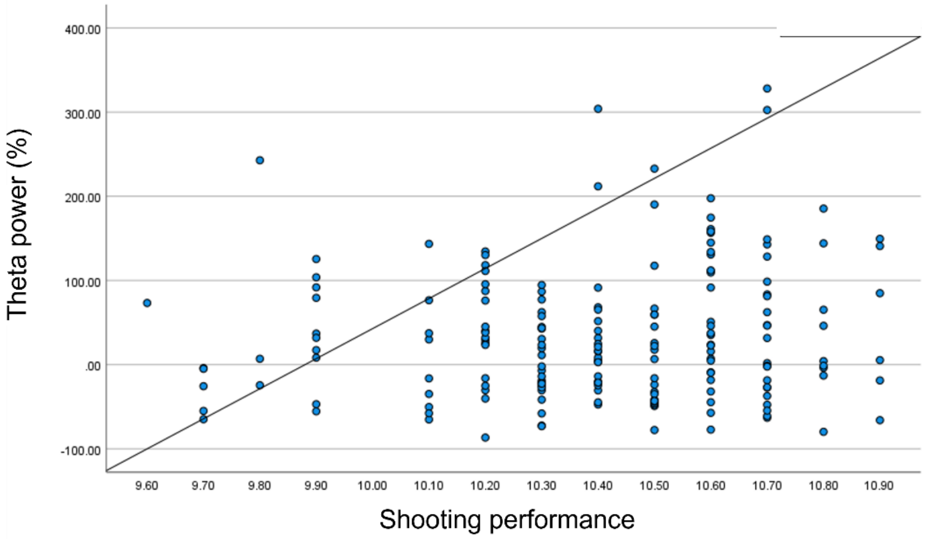


Figure A.2. Relationship between performance and theta (4-7Hz)activity at frontal area during -3000ms to -2000ms.

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