NEURAL CORRELATES OF HIGH VISUOMOTOR PERFORMANCE USING A SPORTING MODEL

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Abstract

The present study seeks to identify neural correlates of high performance in ecological valid, sporting tasks and quantify the differences between high skilled and low skilled players. To do this, Esports is chosen to be the sporting model to facilitate clean brain activity recordings whilst playing sport, something that is considerably more challenging with traditional sports. Participants are first separated into a skilled or unskilled group based on their Esports performance using objective classification measures to identify the presence of a higher and lower performing groups. Their brain activity is then recorded as they complete a series of visuomotor psychophysics and Esports aim-training tasks. Results indicate that there are several key differences in the brain activity of skilled players that facilitate a higher level of performance. Firstly, skilled players modulate visual attention, gated by alpha oscillations, to release the visual system before target onset. As a result, visual information is consciously accessed more readily to be utilized for a motor response. Secondly, skilled players utilize cueing information, received from multi-sensory cues, and propagate it in working memory to narrow visual search and improve performance. Finally, skilled players show an increase in frontal-midline theta during Esports performance facilitating management of cognitive load and repeated execution of precise movements. Due to the nature of the model, applied implications are suggested for both coaches and athletes of all sports to utilize this research. Specifically, performance improvement of players could be facilitated by identifying deficits in their brain activity and talent identification, by observing the neural correlates reported in developing players.

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Firstly, I would like to thank my family for their continued and unwavering support through my studies. Their enthusiasm and belief in me helped me achieve my dreams.

To my girlfriend and partner, your love and happiness brings joy even in the darkest times. You make all our sacrifice worth it.

Finally, to my supervisors Barry and Ole, thank you for indulging my crazy ideas, keeping me focussed and striving for greatness.

List of Abbreviations

Abbreviation		Definition
ACC	-	Anterior Cingulate Cortex
ADR	-	Average Damage per Round
ASD	-	Autism Spectrum Disorder
BEM	-	Boundary Element Model
CS:GO	-	Counter Strike: Global Offensive
DICSs	-	Dynamics Imaging of Coherent Sources
dSPM	-	Dynamic Statistical Parametric Mapping
eDPI	-	Effective Dots Per Inch
ERD	-	Event Related Desynchronisation
ERN	-	Event Related Negativity
ERP	-	Event Related Potential
ERS	-	Event Related Synchronisation
FC	-	Fixation Cross
FM	-	Frontal Midline
FPS	-	First Person Shooter
GLM	-	General Linear Model
IAF	-	Individual Alpha Frequency
ICA	-	Independent Component Analysis
IOR	-	Inhibition of Return
K/D	-	Kill/Death Ratio
ML	-	Machine Learning
MOBA	-	Multiplayer Online Battle Arena
MRBD	-	Movement Related Beta Desynchronisation
MSI	-	Multisensory Integration
MVPA	-	Multivariate Pattern Analysis
PCA	-	Principal Component Analysis
PMBR	-	Post Movement Beta Rebound
TTK	-	Time To Kill
VAN	-	Vision Associated Negativity
VG	-	Video-Game
VGP	-	Video Game Player

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CHAPTER 1

General Introduction

With the professional development of Sport and Sport Science, the branch of performance analysis has become crucial to aid players in their continual pursuit of improvements. What started as simple observations has now become a rigorous, data-driven machine powered by many employees across several disciplines. Those performance analysis departments that are the most in-depth include data from a huge array of sources. It is relatively simple and cost-effective to attach GPS, accelerometers, and other such equipment to players as well as high-definition videography in both training and during competition. This provides scientists with data incomprehensible to the human eye that can be processed, stored, observed, and used time and time again. Furthermore, advances in computing have allowed for the implementation of statistics, advanced mathematics and machine learning across all datasets transforming data to uncover more nuanced relationships between variables that were previously hidden.

With modern technology, it is possible to set up statistical analysis of so many aspects of performance, but by analysing the team, players, and oppositions collectively, it is possible to manipulate the very threads that lead to winning. Whether that is identifying players on the cheap for a precise function, or the best talent that money can buy, team statistics has untold power if rooted in fundamental mathematics with respect to sport in question. Indeed, using mathematical models and statistical propositions to make evidence-based interpretations of performance is a key idea for modern sport science. To identify performance indicators and analyse their impact on a given player, team or sport, one must understand the dynamic nature of each indicator within a mathematical context. Crucially though, this theoretical data cannot be used at the expense of practical sporting experience and knowledge that can only be gained through genuine understanding of the sport (Lames and McGarry, 2007).

Although a wide variety of biomarkers have been used within performance analysis, the most important endeavour is the brain. The human brain is the most complex organ in the living world, yet our knowledge of the brain, however vast, is still incomplete. In sport, this problem is compounded by difficulties recording from players as they play sport in an ecologically valid setting. For example, experiments on elite swimmers are nearly impossible since they are in water, something relatively incompatible with electrical devices. However, science continues to find solutions to this problem using innovative methodologies. Before reaching that point though, one must first consider how brain recordings are possible, and what signal is actually being detected.

Brain activity and electroencephalography (EEG)

Brain activity research on Sport using cognitive electrophysiology is a new and emerging branch of neuroscience. To understand the results of this data, one must consider some of the more fundamental aspects of brain activity. A common step in processing EEG data is to decompose it into either the time or frequency domains. In the time domain, the tradition form of analysis is to look at how the voltage of the signal recorded at each electrode site changes over time whereas the frequency domain observes how that activity oscillates over time broken down into certain frequency bands. Crucially, this activity is temporally localized to a certain event, moments in trials that are marked to represent an important event within each trial. For example, it is very common to mark events within in a trial that signify to onset of the trial stimulus and that mark a response. From here, one can look at event related dynamics in either the time or frequency domain. In this type of analysis, many trials are presented to the participant and the brain activity surrounding it is isolated. The same time-window for each trial is used to remove an equal portion of the activity before they are all averaged together producing an averaged response in either the time or frequency domains.

Event Related Potentials (ERPs)

The typical time domain analysis is called Event-Related Potentials (ERPs). These potentials, when averaged together, can represent brain activity biomarkers of certain behavioural components. Elements of the ERP, such as the latency to a peak and the amplitude of the peak can be used to discriminate between distinct phases in the brain activity processing. For example, an occipital lobe localized p100 (positive increase occurring around 100-150ms after the onset of a visual stimulus) denotes a visual reflex and the early-stage processing of visual information.

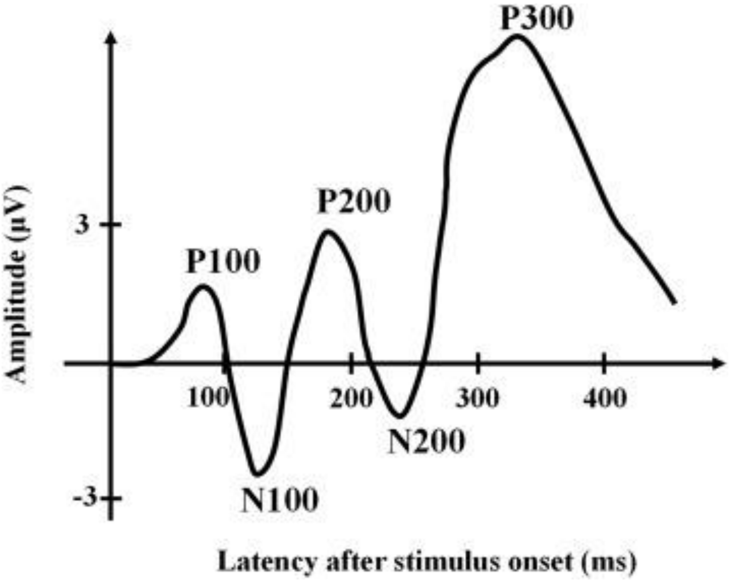


Figure 1.1. A typical event related potential (ERP) displaying positive and negative potentials occurring over time after a stimulus onset. P/N refers to a positive or negative potential in amplitude. The numbers refer to the time at which a peak is observed. Adapted from Baghdadi et al (2021).

P100

The visually evoked potential research has identified the p100, a positive potential detected in occipital sensors 100ms after a visual stimulus onset, as an early electrophysiological correlate of target-orientated visual processing (Desmedt and Robertson 1977). This is a bimodal process with average p100 amplitudes isolated to each eye showing little variability when presented in the same spatial location (Shors et al., 1986). However, by presenting a visual stimulus in different locations in the visual field, significant differences in amplitude and latency in the waveform become apparent (Saba et al., 2023). Increases in target size and a participant’s visual acuity also modulate the amplitude and latency of the p100 waveform, with decreases to latency and gradual increases in amplitude (Li et al., 2011). During continuous visual stimulation, steady state visually evoked potential amplitude increases, but time-locked averages decrease (Rosenstein et al., 1994). This alteration to time-locked evoked potential amplitude is regarded as a substrate for visual habituation.

Early-stage visual processing also has a key contribution to latter stage, more complex cognition. This occurs in both explicitly and implicitly vision-based behaviours. A notable explicit vision-based behaviour is face perception. This process begins early, reflected in the p100 wave form as a face-selective response (Herrmann et al., 2005). The p100 (referred to as an M100 using MEG) amplitude correlates with successful characterization of face stimuli, discriminating them against other visual stimuli, but not with successful individual face recognition (Liu et al., 2013). Sustained spatial attentional mechanisms are also influenced by visually evoked potentials. By presenting a visual target either to the left or the right visual field immediately preceding a continual visual stimulus (in this case, visual gratings), transient VEPs amplitudes were enhanced by sustained attention (Di Russo and Spinelli, 1999). Although sustained attention is modulated by a wide variety of factors, not least neural oscillations, VEPs served as an early marker of attention in the time domain.

Further evidence for the role of VEPs in complex cognition can be found in disease models, where certain mental disorders result in perturbed VEPs. One such disorder is Autism Spectrum Disorder (ASD) whereby the amplitude of p100 is reduced in ASD+ participants (Kovarski et al., 2016; Kovarski et al., 2019). Reduction in p100 amplitude is also detected in patients with schizophrenia (Campanella et al., 2006; Shah et al., 2018). With p100s being successfully used to classify participants between schizophrenia+ and healthy groups (Tanaka et al., 2013). Overall, p100 VEPs represent an early stage of visual processing that is subject to modulation by the size, location, type and duration of visual stimulus as well as the health status of the participant.

P300

One of the most widely studied ERP components is p300. Widely detected across different parts of the brain, occipital parietal p300 is thought to reflect the consequences of conscious perception and in particular, conscious access. The central tenant of this theory comes from studies on visual perception of near threshold stimuli. In this paradigm, participants report whether they have seen a flash or not. Reporting that a flash has been seen is associated with a higher amplitude p300 than trials where participants reported no flash (Eimer and Mazza, 2005 ;Salti et al., 2012; Rutiku et al., 2015). This effect has also been abolished by blurring the visual stimuli, displaying a steep drop in p300 amplitude, and recovered by removing the blur (Heinrich et al., 2010). Source analysis has revealed an increase in p300 activation across occipital parietal sensors during seen trials as compared to not seen trials. Furthermore, rare, oddball stimuli also produce a significantly higher amplitude of p300 than expected stimuli (Bernat et al., 2001) but also habituated reliably with repeatedly matched stimulation (Ravden and Polich, 1998). P300 amplitudes are modulated in several ways. Firstly, perceptual training using audio-visual information increases p300 amplitude however, this effect was only present in older adults and produced no significant changes to younger adults (Yang et al., 2018). Secondly, in patients with mild cognitive impairment, increasing cognitive load prolonged latency of p300 during target stimulus processing (Demirayak et al., 2023). As such, p300 in occipital parietal electrodes is seen as a mechanism for conscious access to visual information.

However, p300 may not be the earliest reflection of visual perception. As discussed previously, p100 is regarded as one of the earliest markers of visual processing, but n200 or Visual Awareness Negativity (VAN) represents a neural correlate of visual detection even in trials where the participant isn’t consciously aware of the stimulus (Merikle et al., 2001). This potential, occurring 200ms after stimulus onset in a negative deflection, is stable in its amplitude and latency regardless of trials in which a flash is perceived or not, and remains despite manipulations to stimulus visibility (Koivisto et al., 2008). It is likely that VAN is generated in sensory cortices and implicated in sensory consciousness (Dembski et al., 2021). VAN thus appears to be a robust component of visual perception but does not influence post perceptual processes or even conscious access. Alternatively, P300 is not a reliable marker of somatosensory awareness but reflects post perceptual processing (Schröder et al., 2021). It can be seen as an index of requirements to allocate attentional resources. Perceptual training using audio-visual information increases p300 amplitude however, this effect was only present in older adults and produced no significant changes to younger adults (Yang et al., 2018). Furthermore, in patients with mild cognitive impairment, increasing cognitive load prolonged latency of p300 during target stimulus processing (Demirayak et al., 2023). Finally, p300s are evoked with higher amplitudes by autobiographical stimuli that is self-relevant such as a participant's own name, compared to control stimuli (Gray et al., 2004). This data suggests that p300 amplitude is subject to modulation by stimulus specific training, self-specific stimuli and is perturbed by cognitive impairments.

Neural Oscillations

It has been proposed emerge from the different functions of the cell to process that information it has received. At the peak of the oscillation, the positive period, it has been suggested that the cell is acquiring information. This is followed by a trough, the negative period, which denotes the cell interpreting the information. As a result, it is possible to build a cyclical model of how neural oscillations function within the cortex, coordinated by pyramidal cells. In other words, the dendrites integrate an electrical signal and transfer it to the cell body via the axon. This movement of electrical charges along the dendrites generates an electrical field. When there are many of these cells in the same orientation and firing in synchrony (active at the same time), then the charge is summed and generates a local field potential. This signal is recordable at the surface.

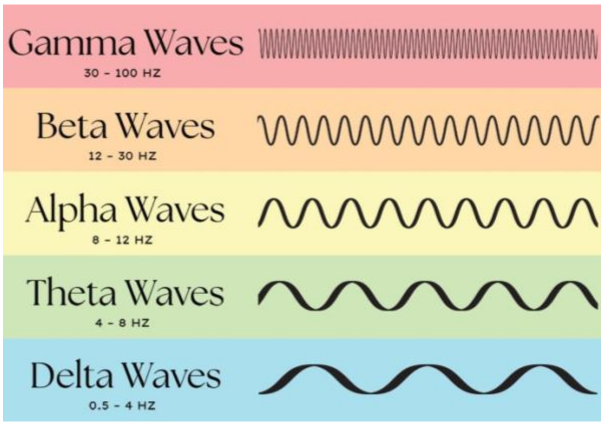


Figure 1.2. Representation of different frequency bands of oscillatory power. There are many types of oscillatory power which provide different functions within the brain. They range from low frequency waves, such as Delta, to high frequency waves such as Gamma. Adapted from https://www.diygenius.com.

Alpha

Alpha is the most widely researched rhythm in electrophysiology. Since its discovery by Hans Berger (1929), it has steadily increased in research focus as knowledge of its importance has intensified. In the earliest research on alpha, there was a general misunderstanding of its nature. Previously, alpha was seen as an “idling” rhythm reflecting inactive neural networks localised to certain sites not active in sensory processing or cognitive processes. The central tenant to this “idling” theory is the observation of power decreases of alpha oscillations after sensory stimulation, but upon disengagement of any cognitive task, there is an associated increase in alpha power (Pfurtscheller , 1992; Pfurtscheller et al., 1996). However, this theory has long since been debunked, not to say that it is untrue, more incomplete.

Alpha oscillations are widely detected across the mammalian brain and provide suggestions on their diverse, but important role in brain activity and function. They have been observed in several cortical areas, including sensory (Bollimunta et al 2008; Craddock et al., 2017)), motor (Sauseng et al., 2009; McAllister et al., 2011) and frontal cortices (Cohen et al., 2008; Ku et al., 2015). However, the area of the cortex most widely associated with alpha oscillations is the visual cortex (see Sewards and Sewards (1999) or Peylo et al (2021) for reviews) where the relationship of alpha to visual awareness has most widely been studied. Synchronous alpha oscillations have been recorded at higher amplitudes deeper into the cortex, compared to high frequency oscillations, such as gamma, often recorded more superficially, when localizing to the ventral stream (Buffalo et al., 2011). It is therefore considered that alpha oscillations facilitate feedback (Bastos et al., 2015; Michalareas et al., 2016) and propagate feedback direction (van Kerkoerle et al. 2014) after receiving bottom-up inputs from superficial neurones carrying high frequency oscillations. Mechanistically, this could be achieved by cells deep in cortical layers directly activating local inhibitory neurons, which in turn inhibit local activity (Olsen et al., 2012).More widely though, alpha oscillations have been associated with propagation of activity throughout the brain across several critical brain areas. A particular focus has been the communication between the thalamus and posterior cortices (Saalmann et al., 2012) and more precisely between occipital, parietal and frontal regions (Sadaghiani & Kleinschmidt, 2016). Each of these sites seem to be linked by information flow and ultimately, communication, facilitated by modulation of alpha oscillations.

Visual Perception

As mentioned previously, alpha oscillations have a strong relationship to vision as evidenced by their prevalence in visual regions of the brain. As such, alpha is a crucial component of visual perception . It is regarded as a fundamental rhythm of conscious perception that plays an active role in sampling information from the sensory world to inform one's internal conscious experience (Babiloni et al., 2006). In fact, by controlling pre-and post-stimulus alpha power using TMS this can differentially impact one's conscious experience of the stimulus. By applying rhythmic-TMS at an alpha frequency pre-stimulus, modulated perceptual accuracy but post-stimulus modulated subjective confidence in the participants decision (Di Gregorio et al., 2022). Furthermore, there are observable individual differences in the periods of alpha that influence the speed at which visual information is processed, with shorter alpha period individual processing faster than longer period individuals (Ro., 2019).

An important finding related to alpha and visual perception, centres around the phase at which a stimulus is presented. If the visual stimulus is presented in the positive phase of the occipital alpha cycle, the probability of perception is maximised (Valera et al., 1981). This effect has been ratified by finding that visual detection thresholds vary with EEG activity phase, particularly in alpha and theta bands, which accounted for a large proportion of variability performance in detecting the stimulus (Busch et al., 2011). This effect may be due to "windows of excitability" created by alpha oscillations, increasing likelihood that a stimulus will reach conscious perception (Mathewson et al., 2009; Duque et al., 2011). The phase of alpha oscillations can determine whether visual signals on a sub-second temporal scale will be temporally integrated or segregated (Wurtz et al., 2014). Short-lived alpha phase synchronization has been found to be critical for integration of transient visual information (100ms) allowing the visual system to remain sensitive to dynamic changes in visual information (Wutz and

Melcher, 2014). This finding is supported by decoding experiments using a rapid visual stimulus task and found highest decoding accuracy in the phase of alpha oscillations (Ranconi et al., 2017).

The peak frequency of alpha shifts depending on the task and state dependencies of the experiment, occurring over small timescales (Mierau et al., 2017). These fluctuations have been positively correlated to cerebral blood flow in visuo-spatial attention networks (Jann et al., 2010). Peak frequency modulations have been observed in a diverse range of working memory tasks, showing a significant increase directly after the task (Angelakis et al., 2004) that can be load-dependent (Maurer et al., 2015) and are localized to the occipital cortex (Haegens et al., 2014). There is also a link between APF modulations and more physically demanding tasks. It has been found that resting state APF increases following a strenuous bout of cycling exercise (Gutmann et al., 2015) and increased during a more demanding conditions in a balance task (Hülsdünker et al., 2016). The observed APF modulations was suggested to be caused by increased attention required by the more demanding balancing task.

The temporal resolution of alpha can also be subjected to modulation and has a relationship to visual perception performance. Faster alpha frequencies have been found to predict more accurate flash discrimination, both between and within subjects (Samaha and Postle, 2015). In a temporal integration/segregation task, participants were entrained using audio-visual entrainment temporally modified to their individual alpha frequency (IAF) peak, with either fast (IAF +2) or slow (IAF -2) frequencies. By entraining participants at a faster frequency of alpha, segregation (searching for an odd element) trial performance improved and at lower frequencies integration (searching for a missing element) trial performance improved (Ranconi et al., 2018). This suggests that upper entrainment shrinks the temporal binding window and sensory processing coordinated by alpha oscillations since temporal acuity improves at this entrainment frequency compared to low alpha frequencies (Marsicano et al., 2023). Therefore, alpha oscillations might represent a temporal element within visual processing that functions to gate perception (Cecere et al., 2015)

Alpha oscillations have been implicated in higher-order cognitive processes, such as decision-making by transmitting prior evidence to visual cortex, a common information flow. During a detection task, pre-stimulus alpha in posterior electrode sites, predicted binary decisions, with the phase of alpha influencing expectations on confidence (Sherman et al., 2016). These perceptual expectations are configured by alpha, which facilitates optimal processing for subsequent information (Samaha et al, 2015). As a result, alpha has been suggested to modulate both pre-stimulus and post-stimulus perception impacting both prior expectations and conscious access (Zazio et al., 2022). A possible mechanism for this is that during an alpha cycle, there is an oscillation in excitability in the visual system, directly influencing environmental processing and facilitation conscious awareness (Mathewson et al., 2009).

Attention

A key cognitive process linked to visual perception and the use of that information is attention. Alpha oscillations have repeatedly been implicated in the attentional processes and served a major role in developing the understanding of how alpha oscillations function.

During sustained attention to visuospatial tasks, alpha power rapidly reduces during visual attention in occipital electrode sites, rebounding when these regions become disengaged (Fries et al., 2009). The power changes to alpha though, might reflect task-swtiching as opposed to general attention. This is evidenced by a large body of evidence showing that alpha power increases in visual regions contralateral to the ignored target, the opposite direction to where attention is focussed (Worden et al., 2000). This effect was significant post-stimulus, when compared to baseline (Kelly et al., 2006) and reliably predicted reaction time (Gould et al., 2011).

Alpha amplitude changes may originate pre-stimulus, beginning up to 200ms before stimulus onset with significant suppress at sites contralateral to attention (Sauseng et al., 2005). This was accompanied by increased phase coupling and long-range synchronisation between frontal and posterior-parietal regions of the contralateral hemisphere but increased desynchronisation in the ipsilateral hemisphere (Doesburg et al., 2009; Foxe et al., 2014). In fact, optimal performance correlates with alpha power decreases in task irrelevant areas, coordinating sensory inhibition and integration by top-down control networks (Jensen & Mazaheri, 2010). Another important aspect of attention is working memory, where research has continually linked it to the role of alpha oscillations. Although, alpha oscillations seem to suppress irrelevant visual information from being attended to (Johnson et al., 2011), alpha power has been shown to increase with memory-load (Jensen et al., 2002), increase during memory retention period (Bastiaansen et al., 2002) and depending on differences in the visual stream activated by the visual information (Jokisch & Jensen, 2007).

Beta

Oscillatory beta activity is an essential constituent of many aspects of cognitive function. Importantly, beta oscillations have been implicated in many characteristics of motor activity, regarded as a general mechanism for this activity, as well as contributions to cognitive state (Engel and Fries, 2010). Beta activity is localized to a number of highly important regions in the brain facilitating its role in general motor/cognitive mechanisms. Low frequency beta (15–18 Hz) is predominately observed in occipital-parietal regions and high frequency beta is predominately observed in motor (~20Hz) and pre-frontal regions (20-30) of the brain (Rosanova et al., 2009; Capilla et al. 2022).

An important process associated with beta is visual perception and attention. During visual perception tasks, beta power has been shown to significantly increase during perceptual switches between two stable pictures, occurring between 250-450 ms (Okazaki et al., 2008). These power modulations are also present during animations where participants switched between local and global motion (Zaretskaya and Bartels, 2015) and in motor integration tasks (Aissani et al., 2014). In more complex tasks visual tasks, such as a crowding paradigm, larger post-stimulus beta power desynchronized, with a greater magnitude in the strong crowding condition, compared to weaker crowding condition (Ronconi et al. 2016). However, this effect may occur due to stronger pre-stimulus beta power which was correlated to correct performance in the same task (Ronconi and Bellacosa Marotti, 2017). Interestingly though, it has been postulated that beta oscillations carry little information directly about the stimulus, but may predominately reflect neuromodulatory inputs (Belitski et al., 2008).

It has been seen that beta power modulations are associated with performance in different visual attention tasks, computed in the fronto-parietal network. Within the frontal eye fields, movement neurones displayed an increase in beta synchronisation but a desynchronisation during a saccade task (Gregoriou et al., 2012). This beta activity was associated with suppression of attentional shifts (Fiebelkorn et al., 2018). An important piece of supporting evidence in a dysfunctional brain can be found in neglect patients where frontal and parietal connectivity is suppressed during visual attention tasks (Yordanova et al., 2017). Furthermore, within this network, there is a correlation between beta-band power and performance within a visual search and motor task at resting state (Rogala et al., 2020). When taken together, visual perception, attentional switching and visuomotor performance are, at least in part, coordinated by beta-band oscillatory power in the fronto-parietal network.

The most famous association with beta power is to motor activity and general motor mechanisms. Beta power increases have been implicated in a number of different types of movement such as static position maintenance (Baker et al., 1997), post-movement holds (Pfurtscheller et al., 1996) and even suppressing movement initiation (Swann et al., 2009). This suggests that beta oscillations are important for the maintenance of motor behaviours (Engel and Fries, 2010). However, this type of approach loses some intricacy of the temporal dynamics of beta oscillations and movement since beta power can shift depending on the movement phase.

MRBD and PMBR

A more refined way to characterize beta based on the movement phase is splitting it into two distinct categories, Movement-Related Beta Desynchronization (MRBD) and Post-Movement Beta Rebound (PMBR) where these two categories reflect movement preparation/initiation (Zhang et al., 2008), and post-movement termination activity (Heinrichs-Graham et al., 2017) respectively.

MRBD as well as resting beta power, has been found to be highly reliable after motor-training interventions across participants, across sessions in both sensorimotor cortices (Espenhahn et al., 2017). There is a significant relationship between MRBD and resting beta power in primary motor areas in addition to MRBD magnitude and movement duration (Heinrichs-Graham and Wilson 2015). This effect may also reflect performance since when reaching, those movements that were preceded by a greater reduction in beta power, exhibited significantly faster movement onset times (Khanna and Carmena 2017). MRBD might also be linked to circadian rhythms due an increase in desynchronisation in the morning to afternoon period (Wilson et al., 2014 (1)). Age appears to also play a role in this process by increasing MRBD amplitude and resting beta power (Rossiter et al., 2014). Finally, supporting evidence of how this MRBD should operate in healthy participants can be found in Parkinson’s and Stroke patients, where MRBD in motor cortices was found to be significantly reduced compared to control groups (Heinrichs-Graham et al., 2014; Rossiter et al., 2014 (2)). This suggests that MRBD is a fundamental mechanism for performing movements since it can influence the onset and duration of the movement but is perturbed in a population where this process is dysfunction.

PMBR is generated in the motor cortex and was strongest contralateral to the side of movement (Jurkiewicz et al. 2006). It serves as a signature of active immobilization after a movement has been terminated (Salmelin et al. 1995) and reflecting movement-related somatosensory processing (Cassim et al. 2001). The amplitude of PMBR is subject to modulation by several different factors of the movement that has just terminated. Specifically, the type of afferent input (Houdayer et al. 2006) such as the rate of force development and the force magnitude (Fry et al., 2016). Furthermore, the amplitude of the PMBR is higher after termination of actual movements compared to suppressed movements or imagined movements (Solis-Escalante et al. 2012). This signifies PMBR to be a type of sensory check after a real movement has terminated.

Theta

Theta oscillations have been implicated in the top-down control of higher-order cognitive processes such as visual awareness, memory and movement (Cavanagh and Frank., 2014). In particular, theta in midfrontal regions is regarded as a mechanism for action monitoring in the brain (Cohen et al., 2016).

The theta rhythm is detected in several cortical structures within the brain (Steriade, 2000). Specifically, ERS and ERD has been observed in separate yet integrative systems, but function in such a way that synchronisation occurs in the hippocampus and desynchronisation occurs in the neocortex (Hanslmayr et al., 2016). Theta is also detected in the visual system where it is hypothesized to serve feedforward information in the cortical output compartment of V1 (Kienitz et al., 2021). A key cognitive process that theta has been implicated in is visual awareness and attention. In visual search paradigms, theta oscillations may reflect attentional exploration and have a relationship to performance (Dugué et al., 2015). Successful and unsuccessful trials had differential relationships to post-stimulus theta amplitude and opposing oscillatory phase pre-stimulus. This is further supported by the finding that magnitude and phase synchrony of theta oscillations was enhanced because of high-frequency visual stimulation (Hamilton et al., 2020). When restricted to a specific target in reactive control experiments, there was a significant enhancement to theta power localized to pre-frontal regions (van Driel et al., 2019). In frontal central regions, activity was strongest during multi-sensory conditions, processing both auditory and visual signals, where attention was divided (Keller et al., 2017).

Like many brain rhythms, theta oscillations have repeatedly been linked to memory in various forms with Klimesch (1999) concluding that theta power synchronisation represents the encoding of new information. In support of this idea, it has been found that theta synchronisation increases with task demand, facilitating more efficient processing (Weiss et al., 2000). In fact, theta power has been shown to increase throughout all phases of memory trials, only reducing at the end, even whilst processing multiple items (Raghavachari et al., 2001). This concept is supported by further studies showing that during encoding of visual information, there were increases to the amplitude of theta oscillations, although this effect was bi-lateral and seems to function opposingly to alpha power, (Sauseng et al., 2004) and displayed increases in long-range coherence (Klimesch et al., 2010). When taken together, these studies describe how theta oscillations in frontal cortical areas display enhanced when performing many different cognitive tasks, including those that involve perception, attention and multi-sensory processing that exerts cognitive control.

Another brain region under the control of theta oscillations is the motor system. When compared with periods of stillness, movement initiation and execution displayed higher levels of theta, present in the sensorimotor network (Cruikshank et al., 2012). The phase of theta oscillations also predicts perceptual performance with these oscillations being phase-locked to movement onset (Tomassini et al., 2017). During visuomotor experiments, an observed increase in theta synchronisation occurred in the midfrontal areas during higher visual feedback gain trials which corresponded to a decrease in force error and variability (Watanabe et al., 2021). Increases in oscillatory theta is also implicated in motor control by being predictive of motor slowing during motor conflict, independent of attentional conflicts and localized to midfrontal regions (Kaiser and Schütz-Bosbach, 2021).

Theta oscillations may also serve a role in motor learning. In latter stages of motor learning and during the movement planning stage, there is an accompanied increase in theta power in parietal regions (Perfetti et al., 2011). This effect is correlated with degree of retention and difficulty (Van Der Cruijsen et al., 2021). The type of learning used might also alter the increases of theta whereby differential learning appears facilitate increases in theta power more than repetitive, early consolidation (Henz and Schöllhorn, 2016). Furthermore, has been found that training in precise movements might alter the spatial dynamics of theta in frontal-parietal areas immediately before movement onset and contain a relationship to performance improvements (Rampp et al., 2022)

Sport Neuroscience

It has been found in many studies that an expert sporting population has an increased visuomotor performance relative to a novice population. However, studies are conflicted about the neurophysiological origin of this performance difference. In one study, they found faster visuomotor transformation in motor areas linked to increased performance as opposed to the earlier visual perception of information in the visual cortex (Hülsdünker et al., 2016). This is further supported by a follow-up study (Hülsdünker et al., 2018) using a similar sporting population of Badminton players where the speed of visual perception predicted EMG onset. Interestingly, motor processes did not provide the link to visuomotor reaction time performance.

It is not just a sporting population where neurophysiological differences have been noted at a population level. Shift workers, especially those working at night, display prolonged latency of visual evoked potentials which is associated with an increased visual reaction time (Hemanalini et al., 2014). Further highlighting the relationship between neurophysiology and performance at a population level. It appears that it is the consistency of the behaviour, or repetition of the movement that induces the changes at a neurophysiological level. Following general practice on visuomotor tasks, there is a correlation between reaction time and somatosensory neurophysiological changes (Akaiwa et al., 2020). Furthermore, modality-specific training can induce neuroplastic changes to improve visuomotor performance, in particular the execution of the response (Yamashiro et al., 2021).

A key criticism of these visuomotor performance tests, especially in a sporting context, is the use of computer-based methodologies. Performance metrics, such as reaction-time, on behaviour tasks such as the go/no-go task, are not representative of the sport the playing population competes in. Despite this, many studies argue that inducing a movement/cognitive demand is sufficiently ecological validity since there is a selective pressure of speed on performance (Hülsdünker et al., 2019). However, sensorimotor transformation demands of a movement on a mouse, to move a cursor on a computer screen, weakens this assumption. It would be far more ecologically valid to test these movements, with their sensorimotor transformation demands in a sport where the demands are the same.

To do this, the experiments will use Esports, a new sport where players compete by playing specific video games. Esports has been chosen because it facilitates an ability to record from the brain in real-time and in real competition due being a no-contact sport played on a computer. Like many traditional sports, Esports place a huge pressure on the visually guided biomechanics required to aim and execute precise movements to manipulate a piece of equipment. However, there is a much smaller range of limb-movements in Esports compared to others, with many movements being micro-adjustments required to update ones aim or body position.

Understanding how precise movements contribute to performing high-skill bimanual tasks is fundamental to developing better training and development strategies. A focus of research in this area has been the use of eye-tracking to probe visual search and fixation behaviours during sporting competition (Vossel et al., 2014). Whilst it was thought that eye-tracking would lead to physical improvement, it has been found that an athlete's cognitive performance and mental state could be interpreted through tracking of eye movements (Bavelier et al., 2012a). A particular focus is understanding the relevant eye-movement strategies employed by elite versus novice players of a particular sport (Womelsdorf et al., 2014; Anderson et al., 2014). In Esports literature, it has been demonstrated that playing video games leads to significant visual attentional processing changes (Bavelier et al., 2012b) and eye-movement performance differences (Prakash et al., 2012). However, only a small subset of eye movements has been tested, with many important contributors not considered.

Live electrophysiological recording of brains in real-time competition is seen as the final frontier for sport neuroscience (Strenziok et al., 2014). The ability to quantify genuine brain activity, not simply infer it, offers new opportunities to study central tenants of sport performance such as biomechanics, training, decision-making and attention. In Esports, research has primarily used two different approaches to EEG data and to differentiate performance, continuous recording of oscillatory activity and event-related potentials (ERPs). Cortical brain activity oscillates within certain frequency bands facilitating a huge number of cognitive processes. In Esports literature, research has focussed on a range of top-down attention control processes (Gong et al., 2015; Pellouchoud et al., 1999) and visuomotor skills (Sheikholeslami et al., 2007). In fact, the best predictor of skill acquisition was the frontal alpha rhythms. This frontally distributed alpha power is a great predictor of learning shown by a strong correlation with steeper improvement of score (Smith et al., 1999). ERPs differ from continuous recording by creating epochs around an event (around 200ms before an event extending to 1.5s after it) and recording the activity from a specific electrode. By presenting this stimulus many times and averaging the response, any noisy data that isn’t phase-locked to the event is averaged out, generating a smoother, event-related response. This facilitates the identification of standardized responses to specific events such as the P300 (positive potential change 300ms after stimulus onset) responding to an occasional target in a standardized sequence. ERP evidence suggests that the faster behavioural reaction times in Esports players can be attributed through faster visual processing (Latham et al., 2013) displaying earlier n100 latencies in occipital electrodes, O_1 and O_2 Brookings et al., 1996).

In a study on martial-arts, Sanchez-Lopez et al (2016) analysed ERP component differences between skilled and novice groups during a sustained attention task. The task called Continuous Performance Task (CPT) required participants to detect the correct arrow orientation out of five possible and produce a motor response to click on the correct one. The skilled athletes displayed significantly larger p100 and n200 components of their ERP response with the highest significance occurring in occipital electrodes (O1 and O2). However, many studies have reported the opposite effect of the one found in the present study. Lesiakowski et al (2017) compared athletes from a range of different sports that requiring varying degrees of visual processing for high performance. All athletes tested were experienced to some degree, but those with the most experience all displayed reduction in their VEP p100 amplitudes compared to less experienced athletes across volleyball, rowing and boxing. Further to this, exercise might have an impact on the amplitude of p100 VEP. After exercise intervals, the amplitude significant decreased in athletes, but increased in sedentary participants

(Bulut et al., 2005). This effect in a subsequent study was not replicated, with no significant changes in amplitude observed after three-bouts of exercise comparing volleyball players to non-athletes (Zwierko et al., 2011).

A slightly more unifying observation in the previously mentioned studies, is the change in p100 latency which has been observed in many studies, both post exercise (Özmerdivenl et al., 2005, Zwierko et al., 2011) and with sporting expertise (Lesiakowski et al., 2017). The latencies of both p100 and n140 ERP components in baseball players were significantly shorter compared to non-athletes (Yamashiro et al., 2013). Furthermore, after extensive training over a multi-year period, the p100 latency of volleyball players was reduced by 2.2ms on average. All of these studies show support for modulations to p100 peak latency through expertise or training, however, these findings were not replicated by the present study. In fact, there was shorter latency to p100 peaks in unskilled as opposed to skilled players. Whilst this goes against the literature, a possible explanation is that the task did not induce typical VEP as is common with the other studies. Specifically, the visual information was not a flashing stimulus but a precise target requiring fine motor skill to respond to, not a simple button push.

Esports and Neuroscience

Esports is the newest and latest sporting craze to take over the world. Its emergence has been rapidly rising over the past 20 years from its inception, accelerated by the Covid-19 pandemic which forced the world inside and halted worldwide sport. During this period, large proportions of the world were left without competitive sport to watch and were forced online. This teed up Esports to emerge as the only competitive sport available to watch for months. Due to the nature of Esports, competitive tournaments, using hosted on local networks, referred to as LANs, simply moved online, as players could compete as part of their team, against other teams, from anywhere in the world, from the comfort of their homes, all the while being steamed for free to millions. Furthermore, the diverse nature of Esports, such that many different videos-games can be played as an Esport, meant that viewers could rotate through many different options at any point. This revolutionary period for Esports catapulted it into worldwide view, transforming the opinions of many doubters about its longevity.

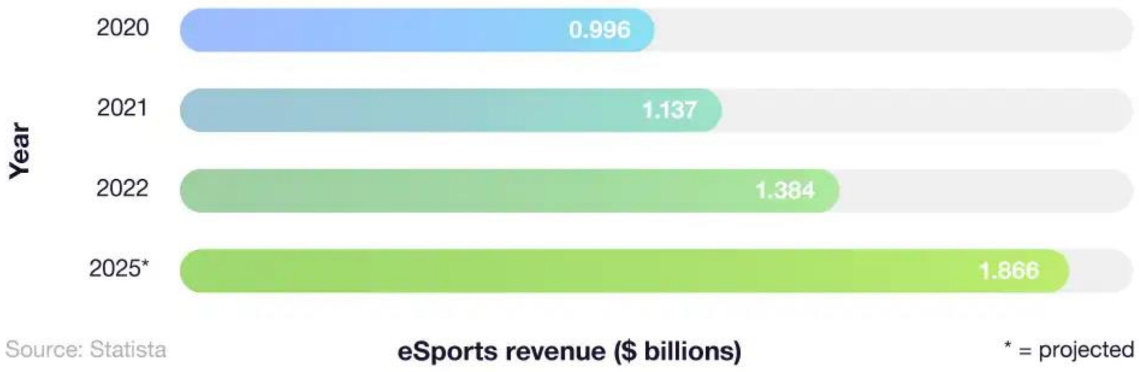


Figure 1.3. Esports global revenue increases in US dollars over a three-year period (2020-2022) with projections for 2025. Data sourced from Statista, figure taken from "Online gaming statistics 2023", Nick Baker, Uswitch.com

In recent years, Esports has emerged into a professional sport with organisations offering paid contracts to highly talented individuals. Academies, coaching services, and psychologist are starting to specialize in Esports competition and creating pipelines for talent to be spotted, nurtured and developed into high-level athletes who can compete on the world stage for vast sums of money. The worldwide public interest seems to emerge from the understanding that Esports is one of the most technically challenging sports around. Although thoroughly modern in nature, Esports differs from traditional sports in that it does not necessarily involve exhaustion of the body. In fact, due to the sedentary nature of the sport, within Esports competition, players can often be seen warming their hands in between rounds to not let them get cold, something rarely seen in other sports. It is the cognitive demand and precise, yet small, movements employed by players that yields the fascination of viewers. As a result, scientific research, especially in the sport-science, sport-psychology, and neuroscience domains, has intensified.

As mentioned, Esports doesn't exert as drastic physical demands on the body as other traditional sports, however that doesn't mean there aren't any physical effects. A key focus within the literature has been on physiological markers of stress during competition, and a key metric being heart rate and blood pressure. During competition, the heart rate of athletes rises to between 102-110 bpm compared to during training where they varied between 80-84 bpm (Rudolf et al., 2016). These findings were ratified by Koshy et al (2020) who found increases to heart and respiratory rate of Esports players during a session compared to a rest session. Interestingly, there were significant increases to mean heart rate and respiratory rate in the winning team, compared with a losing team during this experiment. Furthermore, the videogame or Esport type appears to impact physical parameters too. It has been found that violent video games, in particular FPS and fighting games, increase systolic blood pressure (Siervo et al., 2013, Sousa et al., 2020, Porter and Goolkasian (2019) compared with other video games and/or Esports. These studies demonstrate the relationship to physical impacts of Esports and how these responses are strengthened by competition, compared to rest, and by high-octane, violent videogames.

The most interesting aspect of the physical exertions on Esports and video-game players (VGPs) is the cognitive demands. Such demands induce long lasting changes to cognitive performance that are both significant, when compared to controls, and reproducible. In one meta-analysis of many studies reported improvements to top-down attention and spatial processing in VGPs compared to controls (Bediou et al., 2018). When conducting a variety of cognitive tests, Kowal et al., (2018) found that VGPs favoured a strategy of speed over accuracy facilitated by enhance information processing speed. There also appears to be a VG type specific cognitive enhancement effect, displayed by an increase in cognitive performance across a variety of tasks in FPS players over non-FPS players (Seya and Shinoda, 2016), with this effect being reproduced through an FPS training intervention, as well as faster reaction times (Deleuze et al., 2017). Finally, within Esports players, the skill-level of the athletes, or their rank percentile, shows a correlation with their cognitive flexibility (Valls-Serrano et al., 2022), a key concept to improve performance by modulating anxiety and stress (Han et al., 2011).

As with all sports, VGs and more importantly Esports, relies heavily on vision to facilitate performance. VGPs display significant enhancements to early-stage visual processing compared to controls (Appelbaum et al., 2013) as well as to contrast sensitivity (Li et al., 2009). Substrate for this enhancement sensitivity might be VGPs possessing larger central and peripheral field areas (Buckely et al., 2010). Ultimately, the improvements in visual sensitivity manifest as improvements to fundamental cognitive mechanisms required in all sport such as visual search, in which VGPs show faster response times (Castel et al., 2005) and visual attention (Green and Bavelier., 2003), with these effects being improved in controls with a training intervention.

Interestingly, the cognitive performance of Esports players has been compared to more conventional athletes across a variety of complex tests. Overall, athletes across both sports score very similarly in measures of reaction time, attentional control and memory but crucially, Esports athletes in the speed of visual search (Grushko et al., 2021). This ratifies the use of Esports as a sporting model compared to traditional sports since their cognitive performance enhancements attributed to being an athlete appear to be conserved across multiple areas, and even extenuated in other such as visual search. Ultimately, these studies suggest that it is possible to establish a link between neural and cognitive aspects of sporting performance using Esports as the model (Palaus., 2017), particularly, visual processing, visual search, attention and memory.

Esports provides a methodologically brilliant solution to many of the sport neuroscience issues. As such, research has been able to identify many neural correlates of performance differences to the diverse range of participants who take part in the sport. Attentional networks have been a key source of neural correlates using Esports and VGs, something routinely proven to differ in players. Functional connectivity in attentional networks has been increased due to a VG playing intervention (Strenziok et al., 2014) particularly if playing action VGs centred around the insula (Gong et al., 2015). By increasing frontal-parietal connectivity, players display an improved cognitive control due to enhanced bottom-up reorientating skills within attentional and sensorimotor regions, potentially facilitating many of the cognitive enhancements of Esports players (Martinez et al., 2013).

Further evidence in the attentional network differences comes from ERP components analysis. Behaviourally, VGPs performed better through greater speed and accuracy than novices in target detection paradigms which was associated with a larger amplitude, target-elicited p300 component in VGPs (Mishra et al., 2011). Further evidence for both p200 and p300 amplitude increases in parietal networks have been found after video game training, specifically induced by playing FPS (Wu et al., 2012). However, the p2/300 components, common associated with cognitive workload, show a negative correlation with game difficulty in expert VGPs (Allison and Polich, 2008). From the variety of evidence, attentional ERP components seem to be modulated by player status (game played and expertise) and by the training intervention used. Interestingly, these studies all reporting an increase in connectivity and modulations to ERP components highlighted the role of training intervention regardless of player status, either skilled/unskilled or experienced/novice suggested that playing attentionally demanding games induces neuro-plastic changes to the brain.

Another important substrate of cognitive neuroscience research on Esports/VGs is the role of neural oscillations. As mentioned previously, there are many different rhythms that are important to whole brain function which are required for the performance of complex tasks. By playing video games, the amplitude of frontal theta power increases during playing conditions as opposed to rest conditions (Pellouchoud et al., 1999). Theta power also increases over the duration of playing conditions compared to rest (Sheikholeslami et al., 2007). The theta power increases associated with prolonged VG play was localized to the frontal midline (He et al., 2008). Interestingly, Anguera et al (2013) used a VG training intervention on older participants to improve cognitive performance. As expected, an increase in frontal midline theta power was found during the training but was also sustained – compared to baseline pre training levels – six months later. This sustained power change resulted in performance benefits that were detected outside the scope of the experiment, particularly untrained cognitive control abilities. This collection of studies strongly suggests the role of theta, localized to the frontal midline, in the coordinate of sustained attention required by a complex stimulus such as VGs/Esports and raises the question about its use as a neural correlate substrate of higher performance. However, an important element to note, is that frontal theta power has been shown to be negatively correlated to Internet Gaming Disorder (IGD) severity, something young adults are particularly susceptible. Of course, this is a challenging topic since many professional Esports players would fit the diagnostic criteria for IGD, even though it's their profession. Is frontal theta a biomarker of a gaming dependency disorder or a correlate of playing time?

Beta power, although lesserly, has also been implicated in the performance of players during VGs and Esports. When compared to sitting idly, beta power was higher in occipital, parietal frontal and motor regions during VG play, with these regions being highly coherent of another implying connectivity during play (Malik et al., 2012). Beta power ratio has been found to be significantly higher during an Esports task (car racing Esport) than compared to resting conditions (Hagiwara et al., 2020), however there wasn't a comparison to non-Esports players, so understanding whether this originates from the motor skills required to execute the response or an elevation specifically in Esports players is unclear. A more interesting comparison found beta power increases prior to winning a round in Esports, suggesting its impact beyond single actions and extending to more complex cognition in Esport performance (Minami et al., 2021).

Finally, the most widely studied rhythm, alpha. Strangely when it comes to Esport neuroscience, there is a clear departure from sport neuroscience research which has heavily focussed on alpha power. Most surprisingly is that Esport neuroscience focusses a lot on attention, for which alpha plays a famed role. However, frontal alpha power has been identified as one of the best predictors of learning rate during training on a VG (Mathewson et al., 2012). Together with delta and alpha ERSPs, the use of alpha power as a predictor accounted for 50% of the learning rate variance of the behavioural performance in the task. Furthermore, alpha power has been shown to be higher, localized to motor regions, whilst playing a VG compared to resting conditions, as well as alpha connectivity (Malik et al., 2012).

Gaps in the Literature

From an extensive literature review, spanning a variety of disciplines that cover Sport Performance, Cognitive Electrophysiology and Systems Neuroscience, a few gaps have become evident. These are:

- If differences in performance across skill levels in a population are evident behaviourally, is it possible to explain them using neuroscience?
- Is it possible to apply highly precise cognitive electrophysiology to an ecologically valid sport
- To what degree are neural oscillations implicated in sporting performance of fast, reflexive, sensory dependent movement responses.
- To what degree are cognitive processes, represented by distinct neural oscillations and time domain dynamics different in a skilled population over an unskilled population.

Aims of Thesis

The overarching aim of the present thesis is to address whether there are correlates of high performance in sport, present in brain activity. The main thesis has three main aims, addressed in each experimental chapter.

Firstly, to test whether the visual system responds differently in skilled players compare to unskilled players and to what degree does that impact performance. This is addressed in all experimental chapters, but especially chapter 4. In this chapter, simple visual information is presented over a short time course and players must execute a fast, but precise motor response to be successful.

Secondly, to test whether skilled players process muti-sensory information, differently to unskilled players. This is a phenomenon that is inherent to many different sports and is tested in chapter 5 with an audio-visual cueing paradigm. In this way, auditory information predicts the visual stimulus onset location, but the cue is either presented unpaired (occurring 1000ms before visual stimulus onset) or paired (occurring simultaneously with visual stimulus onset).

Finally, at the highest level of complexity and ecological validity, which brain areas are coordinating a higher level of performance. This is tested in chapter 6. It has been established that theta power is heavily involved in videogame play, but to its relationship to Esports performance is unknown.

Chapter 2

In this chapter experimental methodology and philosophy is introduced to explain to the reader how and why Esports, a new and quickly evolving sport, is an appropriate model to choose for all sport as well as an in-depth outline of how the model is utilized. Furthermore, a deeper description of EEG methodologies and pre-processing steps is included to help the reader understand how the results were achieved.

Experimental Philosophy

Sport science has developed significantly over the past 50 years. Biomedical, technological and mathematical advances have created a diverse and exciting field, focussed on improving the performance of players. However, there is a finite source of information that these approaches will yield. Incredible models have redefined how we observe common assumptions in sport science. For example, using particle physics to explain spatial distribution of players and their intrinsic relationships on a football pitch provide new data, new conceptual philosophies for analysts to explore. However, there is a final frontier. One that could provide a rich source of explanations for performance. The brain.

The human brain is the most complex biological entity in the known universe. Even with all the technological advances, super computers and AI still can’t function in the same way as the human brain. Sport poses one of the most interesting challenges for the brain due to the complexity of information required to play at an elite level. this information can be broken down into different categories increasing in complexity.

Basic information processing in sport comes from the sensory world. Visual and auditory information play a crucial role in all sports providing spatial cues, about a multitude of variables implicit in sport. Take for example a goal kick being distributed in football. The ball may travel for a few seconds and in that time a player must not only analyse where the ball will land, computing attributes of the ball’s movement such as velocity and spin, but a player has to calculate how far that landing spot is from their own spatial position. This information will then be used to inform the motor system about how fast they should move towards it and where to stop.

On top of this more basic sensory processing, higher-order cognitive computations must be made either simultaneously or, at least, within the time window of the ball flight. A player must integrate the basic sensory computations information with the location of surrounding players, both allied and opposed, to decide about whether they should go for the ball or not based on a predetermined tactical approach weighted against an analysis of the current tactical situation. This is an incredibly demanding task for the brain to compute all whilst under the influence of physical exertion and exhaustion.

As such, sport represents one of the most interesting and complex cognitive challenges on the brain. Yet, the enormous number of variables implicated in even a basic sporting process make scientific research a challenge, where the endeavour is always to control, reduce and precisely manipulate variables. This difficulty is further amplified by the eternal struggle in science to produce ecological validity whilst controlling variables in science. Perhaps this is why cognitive electrophysiological research on competitive sport is not as widely studied or powerful as its applications to more general cognition.

The present thesis seeks to address this by unifying experimental methods in cognitive electrophysiology with ecologically valid sporting tasks. However, the difficultly of variable control and precise manipulations in traditional sports remains. Therefore, it is proposed that a representative model of sport is used.

Esports as a model for Sport Neuroscience

Elite sport forces humans to seek the pinnacle of physical and cognitive performance, making it an incredibly interesting phenomenon of human behaviour. Due to the nature of many traditional sports, recording from the brain has been virtually impossible. This is due to several factors such as: amplifier dependence, movement (and saccade) artefacts and physical contact with the electrodes. Furthermore, considering the nature of human bipedal movement, it is very difficult to isolate the neural computations behind movement if as many as four limbs are moving at once. If one considers any type of sporting movement, each limb might have a collective but independent contribution. For example, kicking a ball requires not just the leg that kicks it to be moving with precision, but the standing leg to provide stability and arm movements to provide balance.

Figure 2.1. Football player Steven Gerrard kicking a ball displaying the combined contribution of all limbs for a single action. Isolating how the motor cortex computes a precise leg movement, requires identifying and subsequently removing the contributions to the other, balancing limbs.

In movements such as these, it becomes more difficult to delineate brain activity related to the movement in question since its origins are unclear. Isolating the contributions of the brain to execute this movement, without the associated noise of balancing movements is incredibly difficult and provides a great example of the challenges within sport neuroscience. As a result, the progression of Sport Neuroscience has remained truncated to only post hoc analysis of brains or poorly representative recreations of sporting scenarios. To achieve progression, a better model is required.

Within science, models are ubiquitously used to overcome different challenges with the research focus. In biological sciences, one might use a representational model to overcome the issues with conducting certain experiments on humans. This approach might give significant biological advantages over human models, beyond simply the ethical considerations. For example, zebrafish provide a brilliant model for developmental biology due to their transparent embryos or for genetics, drosophila having a simple, manipulatable genome. Lessons, rules, and processes present in these models can then be applied to humans, having utilized the differences present in the model that made the experiments easier.

To build said model in a sporting context, one must consider two things: brain activity and sporting ecological validity. However, satisfying both demands is not possible with traditional sport. This is where Esports comes in. A new sport, Esports combines several different types of video games, played in a competitive way. Whilst the various rules and strategies in the video games differ massively, the fundamental movements remain similar, just the selective pressures are different. Games such as MOBAs (Multiplayer Online Battle Arena) are slower and require a heavier focus on tactics whereas FPS (First Person Shooter) games, players need to move, aim and react quickly with precision to execute a strategy, placing a heavier focus on the speed and accuracy of movements.

A model using FPS games can be representative of all sports since there is a similar emphasis on fast, accurate movements under pressure to execute tactics, rather than a slower more complex tactical procedures employed playing MOBAs. Interestingly, elite competition on FPS Esports also requires a similar environment to those needed in Cognitive Neuroscience research. That is, participants/players are sat at a computer with stable posture, restricting head and limb movements for robust performance. Going back to the ball kicking scenario, aiming movements in Esports require a single limb to move, with a player’s posture and stability supported by a chair. As such, brain activity representations of movement are limited to only the limb of interest. Furthermore, external environmental variables are also heavily controlled, something significantly more difficult in traditional sports. All in-game environmental information is fundamentally limited to what’s on the screen, narrowing visual search to a precise, measurable area. Lighting, wind, ground quality are all factors that are not present in Esports. Opposition movements can also be precisely controlled, constrained, or made to be precisely reproducible every time. All these external variables are not present or can be precisely controlled in Esports, an advantage not possible with any other sport.

Whilst playing Esports, certain actions in game trigger other events, similar to how certain psychophysics experiments are conducted. Similarly, good performance in FPS Esports has a selective pressure of a fast reaction time and few errors, common performance metrics in psychophysics experiments. This allows FPS Esports to be used as a representative model for Sport but also retaining the essence of a psychophysics experiment, a precise way to access event related brain activity changes.

As a result, the visuomotor performance of skilled Esports players could be used to pinpoint the neurophysiological origin of good performance in a highly ecologically valid sport-derived scenarios. To achieve this a series of experiments are proposed dissecting performance of players, across several different tasks whilst recording brain activity and eye movements.

Brain activity and electroencephalography (EEG)

There are a quite a few ways in which brain activity can be recorded and imaged that are readily used by researchers in the cognitive approach to neuroscience. One of the oldest, cheapest, and powerful is EEG. Pioneered by Hans Berger (1929, 1931), his use of electrodes placed on the scalp of human brains recorded electrical activity. Although he only used two electrodes, placed frontally and posteriorly, this sparked a new generation of neuroscience, stepping away from the typical approach of other neuroscience pioneers like Ramon y Cajal who focussed on neuroanatomy through cell culture and staining work. By taking this approach they were able to progress research into intact, behaving humans and generating real recordings of the dynamics of the brain as it functions. Although his first conceptualizations of neural oscillations in the brain have been completely reworked into the precise theories of today, the world of cognitive neuroscience and its now diverse approaches and modalities, owes a huge amount to Berger. Before moving onto the theories that have since developed, it is first imperative that one understands the origin of the signal recorded from EEG.

Like all tissues in the human body, the brain consists of a myriad of complex cells that are active together to complete a certain biological function. In the brain, the most complex organ and tissue in the mammalian body, there are many biological functions that are executed, monitored, and processed here. Cells in the brain come in many different types, but the two most important are Astrocytes (supporting cells) and Neurons (nerve cells). Whilst the function of Astrocytes is continually unravelled, it is a far less studied cell type since it has less of a contribution directly to cognition, more providing a supporting role. Neurones, the main consistent cells of the all the central nervous system (CNS) but predominately nerve fibres, are incredible, powerful cells. They deal with a wide range of activity but are the functional unit of brains. It is from neuronal activity that electricity is generated. Whilst incredibly complex, the simplest aspects of the activity have been solved for many years. From a cellular perspective, electricity is generated during an action potential. This is where the signal in a neuron travel down the cell to be communicated to another one. The process of this is best described using a particular sense. In this way, we can start from primary reception of information and follow how that information is then transmitted to another neuron. After an initial action potential is generated in primary receptive tissue (such as a retina), action potentials are passed down from neuron to neuron through connections called synapses. It is here where processing takes place.

When recording brain activity using Electroencephalography (EEG), the electrodes are placed on the scalp of a participant. At the scalp, electrical activity is detected that originates from neurones wired into circuits and function within region-specific systems. However, the electrical signal detected differs from those found using cellular electrophysiological techniques, such as patch-clamp. In fact, the signal is referred to as an electrical field or scalp potential. In scalp potentials, there is local synchronous activity from certain neighbouring regions being active together. These regions produce a small voltage change which, when summed across many aligned active neurones – in certain cases anywhere from millions to billions of neurones – can produce a signal large enough to be detected at the scalp. In particular these, neurones are called pyramidal cells and are key cellular and structural components of the cortex. These cells must be radially orientated to the surface of the cortex, synchronously activated, and aligned in parallel to be recorded as a net positive potential.

Such is the nature of the mammalian brains, isolating signal independently from other signals is incredibly difficult. The activation of single, aligned sets of neurones will not come without activation of other neighbouring electrodes each coupled with its own unique significance to the ongoing cognitive process. As a result, an important endeavour of processing EEG data is separating these differing parts of activity. A common feature of EEG data is detecting electrodes that increase in voltage at a certain point and another electrode decreasing in voltage at the same time point. An important feature of the pyramidal cells is that they receive both excitatory and inhibitory inputs from an array of different cells that make up the cortex for many purposes, for example glial cells.

EEG Data Acquisition and Analysis

To capture the performance of players whilst playing commercially built Esports, Weblink (SR Research) was used. Using Weblink facilitated several key aspects for data acquisition. Namely, it allows for the presentation of instructions to the participant, calibration of the participant with the eye-tracker and captures what occurs on the screen. Importantly, through a parallel port device (LabHackers), transmission of TTL event markers between the display pc, the eye-tracking host pc and the EEG amplifier. These event markers are used to epoch the data.

Within cognitive electrophysiology, taking data from its raw form to a fully processed, visualized state ready for interpretation, is a long and relatively arduous process compared to other forms of neuroscience. Fortunately, this process can be streamlined into an automatic pipeline, iteratively processing each file, saving it in each required format ready for processing and interpretation. To get to this stage, many steps are taken and described below.

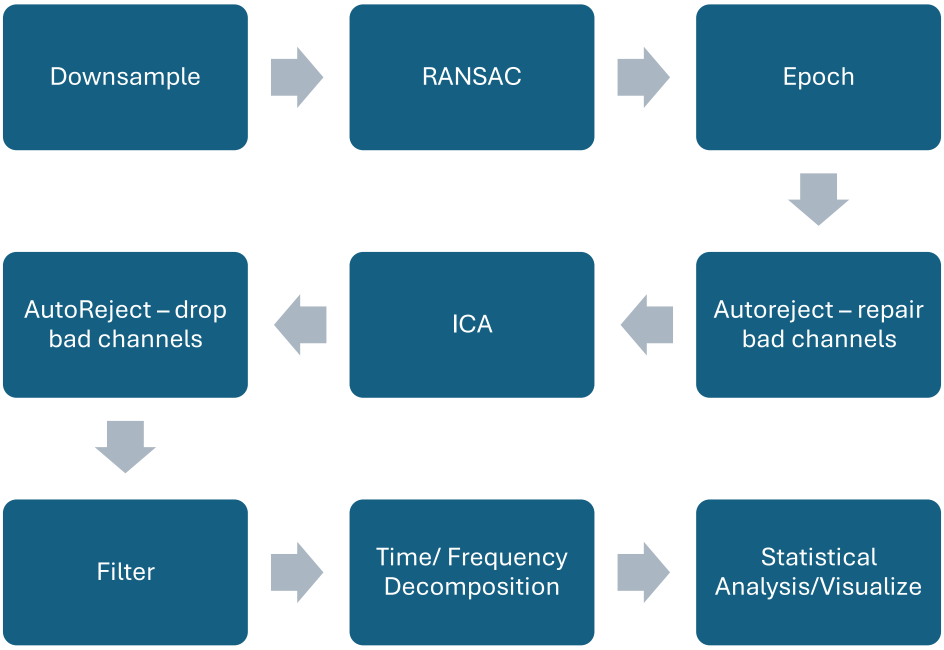


Figure 2.2. The steps implemented across the pre-processing pipeline used for data-analysis within this experiment.

RANSAC

After first down sampling the data to a more manageable sampling rate (from 2048 – 200Hz), the RANSAC algorithm is applied to the raw data. Firstly, RANSAC was performed on the original signal to detect bad channels, remove them and interpolate the remaining channels to reinstate the original subset. EEG data often contains sensors that are locally very noisy, either periodically or throughout the experiment. To rectify this for a specific channel, one can add more conductive gel, however, this is a slippery slope and has the potential to disturb other sensors that were previously acceptable, but with the addition of more gel, will cause them to bridge to one another.

Due to the nature of these experiments (inducing saccades and fast movements), noisy sensors may only become apparent during the experiment when it is already too late. As such, as post-hoc method for dealing with local noisy channels, removing their effects from grand averages is incredibly powerful.

After RANSAC has been performed and noisy channels removed then interpolated, the data can be epoched around certain events of interest. This is performed by using the signal passed through the trigger channel (channel 65 in the present case), and identifying the event specific signal sent by it to denote moments of interest. Typically, the present collection of studies uses different events for: Stimulus Onset, Successful Response and Failed Response. Marked to millisecond precision, the signal denoting these events allows one to epoch around them, taking two seconds before and two seconds after its occurrence.

AutoReject

Once epoched, the data the passes through another automated algorithm called AutoReject, which functions to reject and repair bad epochs which are the basis for trials after being fully processed. To identify bad epochs, AutoReject estimates the optimal peak-to-peak threshold using cross validation. This information is then passed forward to estimate the threshold for each sensor which can then be used to repair through interpolation or, if the threshold is simply too large, excluded from the analysis. Once a first pass using AutoReject is complete, independent component analysis is then applied to the data to identify repeatable artefacts within the data. After the completion of ICA, the data is passed through AutoReject once again as a final check for any noisy epochs. This is a final step where noisy epochs, marked now as *bads*, have not been recovered either by AutoReject or ICA algorithms and thus need to be dropped from the data.

ICA

Independent component analysis (ICA) has become an incredibly powerful and widely used techniques within electrophysiology data pre-processing pipelines due to its sensitivity at detecting artefacts within the data. Within mixed source signals, ICA decomposition can estimate independent signals within the source data of unknown ratios. Typically, before ICA decomposition, as performed in the present pre-processing pipeline, the signal is first scaled to unit variance before using principal component analysis to whiten the data. These steps scale the data by the standard deviation of all the channels, passing the scaled principal components to the ICA algorithm. ICA then separates detected artefacts from brain signals, something it has been reported to accomplish successfully (Barbati et al., 2004). Predominately, ICA is looking for non-brain activity related components of the signal that can be removed. It performs this by comparing the similarity of the components to expert identified components which have been marked as artefacts. Once a match is found to a suitable level, this artefact is marked for removal. Artefacts of interest are eye-movements, heartbeat and non-brain activity related noise.

Average Referencing

Throughout the history of EEG research, active reference electrodes have been used to measure the difference in electrical potential between it and all experimental electrodes. To achieve this, the signal recorded at the reference electrode is removed from the signal recorded at the experimental electrodes individually as a pre-processing, corrective step. In this way, reference electrodes have been chosen to capture electrical activity at the scalp that is non-brain related, isolating it and removing it from the experimental electrodes that will be capturing both the artefactual signal and genuine brain activity related signal. Thus, environmental noise and interference can be effectively removed from the experimental electrodes, making re/referencing an incredibly strong signal cleaning technique. Typically, a mastoid reference has been used since it will capture the interference around the head but placed in a location that will not detect brain activity. However, recently average referencing has been shown to be a more effective solution when performing source modelling, a key processing step in the present studies. This is because a single sensor reference spreads the forward model error into all sensors, which can artificially amplify the importance of this sensor when computing source estimates. However, average referencing spreads the error evenly across all computed channels, preventing uneven weighting during the estimation process.

Experiment Flow and Design

To achieve a true dissection of Esports performance and elucidate the neural correlates of skilled performance, different techniques are required to be employed to detect them. The series of experiments seeks to create an understand of two important concepts within sport performance. Firstly, how does a player extract information from the environment. As has been mentioned, to perform well within a sport, task-relevant information must be extracted from the environment. That information could start basic, such as visual detection but increase in complexity once context is added. For example, visual detection of ball movement close to the player involves simple reflex visual processing, however, this information becomes more relevant based on context, such as if that balls movement might lead to an attacking situation, therefore, within the sporting context, danger. The second concept is how players then use that information to produce a motor response which must be quick, accurate and precise but made under pressure within the framework of tactics. Continuing the example, once the ball movement is detected and a contextual danger cue understood, a player must turn and sprint towards the ball enacting a response. These two processes are, as of yet, inaccessible to common sport science techniques. Careful consideration is also a necessity for the participant, since the goal of the study is to probe human performance. As such, the needs of the participant must be placed highly on the list of priorities, and an environment conducive to high performance is required. To facilitate this, the experiment methodologies and flow are designed with the main aim of allowing participants to perform as greatly as possible.

Achieving a high level of performance within any sport first requires some form of a warm-up, which primes the muscular skeletal system, metabolism and cognitive functions that will be required within the sport (McGowarn et al., 2015) whilst also helping to prevent injury (Franklin et al., 2006). In the specific case of Esports and the present studies, warming up has two important functions. First, it primes the body ready for performance by introducing the brain to the sensory stimuli that participants will respond to and to the type of movements that will be induced. Secondly, it allows participants to become accustomed to the experimental testing environment.

Although the environment has been designed to minimise disruption and disturbance, some of this effort, and the recording modalities, make this more difficult. The participants take part in the experiment in a private sound booth, minimising sound from the external environment. Within this sound booth, the light is turned off to benefit the accuracy of the eye-tracker with the only light source coming from a small window behind them and from the display monitor. Finally, the use of a chin rest and a 64-electrode EEG system means that participants must get used to constrained head movements, robust posture and the sensation of a high-density EEG system being fixed to their scalp. As such, the experimental flow allowed for this, introducing warm up exercises to ease the participant into the study, either with a basic psychophysics eye-movement test (Study 1) or fun aim-training exercises using a commercial aim-training software (Study 2).

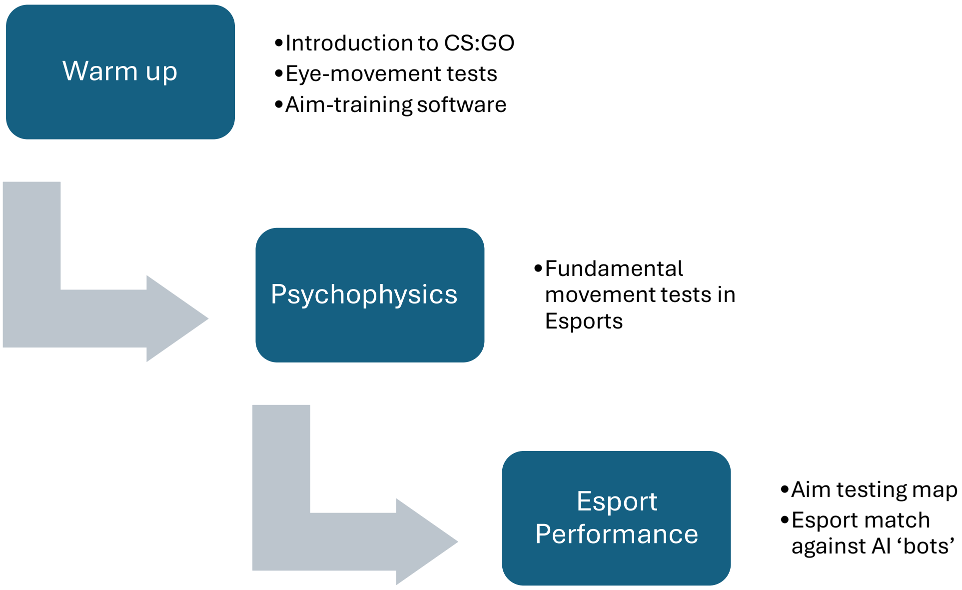


Figure 2.3. The experimental flow of both the studies. A general warm up exercise starts that can consist of eye-movement tests or aim-training using a commercial aim-training software called AimLab. That is followed by the bulk of the experiment consisting of a variety of psychophysics tasks that present simple sensory stimuli to induce Esports related movements in a single action basis. The end of the study used a

complex Esport performance task, either isolating Esports movements within the physics engine of the Esport, or a full competitive match of the Esport against AI-controlled ‘bots’.

To warm-up, players were first introduced to the Esport in use, Counter-Strike: Global Offensive (CS:GO) by loading into a competitive game and playing against the AI-controlled opponents, termed as ‘bots’. Although they only played a single round, participants would be introduced to the game scenario, the way the virtual ‘guns’ would shoot, how to aim with the mouse and how to move around using the keyboard. Within the Esports community, these concepts are referred to as the mechanics of Esports. However, it also allowed players to be cognitively primed for the experiments to come. Notably, detecting targets visually, using that information to guide a movement response that is under the selective pressure of time, since the game is built on the foundation of ‘killing’ the opponent in a *kill or be killed* scenario. Importantly, this reinforced players to be respond as fast as possible or they will fail, a key concept within the psychophysics experiments.

After completing the CS:GO tutorial, participants would then complete an eye-movement test, inducing saccades towards a target direction, with success or failure being predicated on whether the fixation location of their eyes was within the confides of the target border, termed an Interest Area. This experiment also introduced the general flow of the psychophysics experiments. Namely, fixation cross, target onset, outcome feedback. By bedding this procedure in early, participants were accustomed to it when the full psychophysics portion started. In the second study, a further warm-up exercise was used to prime the cognitive and muscular-skeletal systems more aggressively. To do this, a commercial aim-training software called AimLab was used. AimLab has created a wide variety of aiming tasks for players to use to improve performance and captures performance metrics to help facilitate this. Importantly, this portion gave participants a short window to achieve as higher score as possible based on the rules of the task. As such, cognitively, participants were being primed to respond against a timer and movement-wise, they had to respond to many targets across the breadth of the screen. Both elements were important in the subsequent experiments.

Figure 2.4. The use of AimLab by Esports players. ‘Tenz’, a professional Esports player, uses AimLab to warmup on stage at an Esports tournament. Taken from www.AimLabs.org.

After completing the various introductory and warm up exercises, participants would the enter the Psychophysics portion of the experiments. The psychophysics tasks test different elements of aiming, speed and accuracy across the two fundamental aiming movements in FPS aiming. The two aiming movements are Flicking, a fast reflexive movement to a fixed location and Tracking, a slower, continuous movement following a moving target at a repeatedly updating location. Interestingly, the two limb-movements map directly onto the two fundamental eye-movements, with flicking being mapped to saccades and tracking mapping to smooth pursuits. As such, study one focussed on flicking and saccades with study two focussing on tracking and smooth pursuits. Different tasks for each experiment were created to induce the respective limb movements with different sub modifications to the movement.

To create these tasks, the stimulus presentation software Experiment Builder (Eyelink, SR Research) was. All the psychophysics tasks start with a fixation cross (FC) that centralizes vision for the first 1000ms of the trial. After this period, a black target appears somewhere on the screen, a set distance from the FC. The black target was a huge contrast to the white background allowing it to stand out prominently. The trial ends when the participant moves the cursor of the pc to the target location and clicks on it. The click is only registered if it is within the target perimeter. The differences between the two tasks come from the size, location and appearance duration. Players were motivated to succeed by a message stating “move faster” if they failed a trial and “well done” if they succeeded.

Esports Aiming Test and Match

After testing how a simple movement with simple visual information was performed, it was necessary to step up the complexity of both the movement and the visual information, whilst retaining the control of key variables (specifically opponent behaviour).

Two different tests for this were implemented across the two studies to implement some of the ideas, movements and concepts tested during the psychophysics portion. However, the crucial difference is that within the Esports portion, the in-game physics was now in play. Namely, the visual scene was complex and ‘naturalistic’ - in the sense it was natural for the Esport - with backgrounds, complex colours/lighting, human body shape and features. Furthermore, guns had a weight to them, with heavier guns slowing down movement, they also had recoil when shot meaning participants would have to account for this in their aiming to remain accurate.

Esports Aiming Test (NAM1)

Award for neutralizing an enemy with the USP-S
mikeneuro : !PULL
Award for neutralizing an enemy with the USP-S
mikeneuro : !PULL

Figure 2.5. NAM1 map visuals displaying a central fixation cross and targets who appear from behind walls.

NAM1 is a custom-built CS:GO map using source engine programming (Hammer Editor). The map is designed as a shooting-range, where targets appear from specific locations, at specific distances and players must shoot the targets with a specific gun to progress through the trials. To succeed in a trial the player must *kill* the opponent (an AI-controlled *bot*). The map was split into three rows of target locations, with six possible locations a target could appear from on each row. The players started the experiment by completing a warm-up using each gun three times before starting with the Pistol.

In this context, it's important to note that *killing* can be traded for *score*, semantically. Essentially, when each bullet fired from the gun by a player hits an opponent, it counts for a certain *score*. To *kill*, one must hit the opponent enough times so that their score reaches a certain threshold. Once this threshold has been reached, the opponent dies or more literally, de-spawns. Importantly, the location each bullet hits on the character model of the opponent influences the *score* each bullet achieves. Bullets hitting the head count for the largest *score* whereas bullets hitting the extremities like a hand or a foot, count for the smallest of *scores*. As a result, it is possible to view the *score* each bullet achieves as *damage* each bullet does. In this way, a player must do enough *damage* to *kill* the opponent. Therefore, to *kill* an opponent quickly, a player must balance hitting the highest *score/damage* locations whilst shooting fast. In this way, FPS Esports offers a novel motor challenge compared to other sports where both speed and accuracy are a direct relation to performance.

A further layer of complication comes from the guns used. Different guns inflict differing amounts of *damage* and have different multipliers of *damage* depending on where the bullet hit. For example, the Rifle used has a huge headshot multiplier meaning a single headshot will *kill* the opponent whereas the Pistol will require several headshots to *kill* the opponent. This is reflective of the differing amount of *damage* done per bullet shot from each gun, influencing the tactics behind each guns use, and the type of gunfights encountered. Indeed, the sniper is a one-shot kill anywhere on the torso or head (but not extremities) making it the highest *damage* gun. Players will thus modify their tactics to be suit the damage of the gun in use. Furthermore, the speed at which a gun shoots also modifies tactical approach. A good example of this is the Sniper which shoots a single bullet with slow reload times, compared to a Rifle which shoots a high number of bullets very quickly. This places a different selective pressure on speed or accuracy based on how the gun operates and directly impacts a player's cognitive approach to achieve a high performance. To reflect the differing damage and the differing tactics employed when using each gun, the distance to the target row was manipulated. The distances were chosen to reflect common gunfights experience when using the weapon. In order of shortest to farthest: Pistol, Rifle, Sniper. Once 30 *kills* were achieved by the player using a certain gun, they proceeded to the next.

Esports Match (Mirage)

To test performance at the full sporting complexity level, participants played a competitive *bots* (AI-controlled opponents) match on CS:GO. The match is out of 30 rounds and each round is won by detonating the bomb, diffusing the bomb or eliminating the opposing team. The map (Mirage) has two bomb sites which a player must either attack, or defend, depending on which side they are playing on, either terrorist or counterterrorist. Players will play a total of 15 rounds for one side and then switch. In this way, the Esport can be seen as attack versus defence. Players manoeuvre about the confines of the map, looking for other opponents and attempt to plant/defuse the bomb. As with all FPS Esports, visual search is a crucial cognitive strategy required for high performance since blind corners, hiding spots and covered angles make visually discriminating a opponent very difficult. One spotted, a player will then engage in a gunfight, shooting at the opponent. As described above, the player needs to hit enough shots on the opponent to inflict a threshold value of damage to eliminate them. The performance metrics captured by default were used to quantity an players performance. K/D Ratio is the number of *kills* to *deaths* occurred across the entire match. Match Score Differential is the No. of round wins for the players team – no. of round wins for the opponents, across the match. Round win % is the percentage of rounds won by the player. Score per round is the points awarded per round for round contributions such as kills, bomb plants/defusals and winning the round.

The Esports portion of the experiments offer a complex cognitive challenge for all players. In particular, the sensorimotor adaption required to *fire* the guns. By using real-Esports and their associated in-game physics, players must manipulate a mouse to accurately aim but also to naturalistic gun-control elements such as recoil. That is, to accurately shoot a fun with high recoil, a player must not only place their crosshair in the correct location, accounting for bullet drop over distance and opponent motion, but counterbalance the effect artificial effect of recoil. In the real world, shooting straight might require a player to move the mouse in a counter-intuitive way.

Chapter 3

Introduction

Sport is played all over the world at a wide variety of levels. For the most part, sport is played by amateurs, recreationally. For a select few, sport becomes their professional with all the associated money, fame and glory received by becoming one of the best players of that sport in the world. The pressures associated with this, but the incredible gains, serve as a huge incentive for young players to dedicate their lives to attaining this goal.

To become an expert in a specific sport, a player must master so many different elements of it through many hours of practice, with the regularity of training being a key differentiating factor in advanced players (Baker et al., 2015). It has been found that even by the age of 18, international players have accumulated thousands more hours of practice, compared to lower-level players (Helsen et al., 1998). However, high levels of practice do not necessarily result in expert performance (Hodges et al., 2007), but targeted, deliberate practice is far more likely to result in performance improvements (Ericsson et al., 2006), transitioning players to become experts.

Sport science has repeatedly used the expert-novice paradigm to research performance differences in either sport-specific tasks or more cognitive tasks. However, this approach is too vague since there is no definitive identification of what makes a player an expert or novice (Baker et al., 2015). The comparison is both arbitrary and relative, something precisely unscientific. Throughout the literature what makes a player, athlete or team an expert is not consistent, with experts referred to as anything from club level amateurs (Voss et al., 2010), nationally ranked (Bertollo et al., 2012) all the way through to Olympic athletes (Grant & Schempp, 2013). As such, a more robust method must be proposed whereby players/participants are separated not by their supposed group but on performance indicators.

To understand the neural correlates of a higher performance, it is imperative that the populations are distinguished between high and low performance. Achieving this with consistency across a multitude of tests is difficult and subject to experimenter bias. One potential route is taking the top 50% of performers in a task and defining them as the high-performance group. This would give a balanced sample size, uniformity in approach to all tests and ensure that, mathematically speaking, only the highest performers are included in the top group. However, there are several issues with this approach. By taking a range of participants – or players in that sport – there will be some who perform exceptionally, and some who perform poorly, producing maximal separation. But what about the midline? With this technique, the higher performance group (top 50%) might contain players that are distinctly average, showing very little association to the players in the upper quartile. As such, one would then assume, and is a key philosophy of this thesis, that their brain activity would be different. Therefore, this would not be an appropriate technique to separate players into a high and low performance population.

A second potential option is to separate players based on experience level. In this method, players self-report their experience with a sport, both historical and current activity in the sport, and this information is used to define the population. Sample sizes may be subject to imbalances in this method, but the separation between a high and low performance might be more achievable due to the assumption that greater experience leads to greater performance. However, it is well known that experience within a sport, does not necessarily lead to a higher performance in all cases. Some players, for whatever reason, simply do not develop into a higher level of performance, let alone the elite level. Furthermore, definitions of experience are not without their problems. Take, for example, a player who grew up playing a sport, but hasn’t played for 10 years. Are they experienced or inexperienced? It would not be fair to then compare that player to someone who plays every day or someone who has never played before. Again, with the extremes in the population, this technique is adequate, but with most players, this technique is ineffective.

However, in Esports there is a particular problem of players overestimating their ability. This perturbed self-perception occurs in experienced players who are stuck in a low rank. Essentially their self-perception comes from their experience with the game, claiming that it’s the fault of their teammates, issues with their equipment, faults with the game or even cheating. These are often self-truths, understandings of the situation based on feeling not facts. As such, self-report, especially in Esports regarding performance level is not an appropriate separation (Aeschbach et al., 2023).

The aim of the present chapter is to differentiate the population into groups based on skill level. This objective measure will use their performance during a battery of Esports and Esports related tasks. By classifying players in this manner, later chapters will be able to isolate neural correlates of high performance based on the skill level of participants.

Methods

The philosophy of this techniques is to identify skilled and unskilled players based off their performance across a range of tasks that combine many elements of the sport.

Participants

All participants used in this study were university students at University of Birmingham. In study one, 37 participants (15 Male, 12 Female) took part were included and in study two 43 (26 Male, 16 Female) were included. Initially, players are separated based on their current experience level with Esports, not historical experience. This is performed by a self-report questionnaire asking “Do you play Esports for one hour a week?”. Answering yes to this question defines participants as an experienced player, answering “No” to this question defines participants as an inexperienced player. Separating players in this way does not account for any complicating variables such as experience with video games or historical experience with Esports. As such, the classification methods employed will be sensitive to identifying if there is a measurable impact of experience.

Experimental Procedure

After initially separating participants into an experienced or inexperienced group, participants took part in several experiments testing various visuomotor cognitive tests and aiming performance tests. These experiments increased in complexity to develop a holistic understanding of a player's aiming performance, and then their full Esport performance. The performance on tasks described below are then used as inputs to test for the presence of groups.

AimLabs

To test performance in a novel, Esports related aiming task, the commercial aim-trainer, AimLabs was used. This was the first task that participants took part in and served as a warmup, allowing players to familiarize themselves with the experimental environment and get comfortable. Participants took part in three different tasks which were designed to train performance of one of the fundamental movements in FPS Esports. These are flicking, fast reflexive movement towards a static target, or tracking, a slower continually updating movement to a moving target. Each task tested this movement in slightly different ways, facilitating a more holistic understanding of the participants aiming ability.

Psychophysics

After completing this task, participants would then complete the battery of psychophysics tasks used to precisely manipulate and record brain activity. Using psychophysics tasks that a custom programmed, allowed for a few key methodological benefits for concurrent EEG and eye-tracking. Namely, the use of triggers to signal events. These tasks were designed to recreate certain aiming movements, with a drastic reduction in visual complexity, but also in a single action way, diametrically opposed to how AimLabs works. Participants would complete 100 trials per psychophysics task.

NAM1

To increase the complexity, and test performance of aiming movements within an Esport but in a controlled manner, a custom-built CS:GO map was designed using source engine programming (hammer editor). The map is designed as a shooting-range, where targets appear from specific locations, at specific distances and players must shoot the targets with a specific gun to progress through the trials. To succeed in a trial the player had to *kill* the opponent (an AI-controlled *bot*). The performance metrics captured are used to quantify performance. TTK is the time from bot spawning to bot death. Headshots is the number of headshots. Accuracy is the percentage of shots hit/missed. No. of shots is the number of shots taken overall.

Mirage

To test performance at the full sporting complexity level, participants played a full competitive *bots* (AI-controlled opponents) match on Counter Strike: Global Offensive (CS:GO). The match is out of 30 rounds and each round is won by detonating the bomb, diffusing the bomb, or eliminating the opposing team. The metrics captured by default were used to quantity an players performance. K/D Ratio is the number of *kills* to *deaths* occurred across the entire match. Match Score Differential is the No. of round wins for the players team – no. of round wins for the opponents, across the match. Round win % is the percentage of rounds won by the player. Score per round is the points awarded per round for round contributions such as kills, bomb plants/defusals and winning the round.

Statistical Analysis of Behaviour data

All statistical tests were completed using Prism (GraphPad) and the principal component analysis, silhouette scoring and k-means clustering was performed on Python. Statistical analysis predominately consisted of 2-way ANOVA computed to compare Task x Population

Experimental Process

The new methodology is used to determine new populations of participants where performance is maximally similar within the group, but maximally different between groups in a robust, repeatable manner. To do this, the first step is normalizing the data.

To compare a widely differing array of data, from different sources, different experiments and different metrics, normalization is imperative. Normalization of data, alters its scale to fall between 0 and 1, improving the performance of machine learning (ML) algorithms, something very beneficial for this method. This occurs because ML algorithms converge faster when features are on a smaller scale, creating better post-training coefficients, improving computation accuracy and reducing computation time. In this way, the ML algorithms are less sensitive to the scale of the metrics. In the present case, scales can vary from tens of thousands (e.g. AimLab score) to >1 (e.g. Errors).

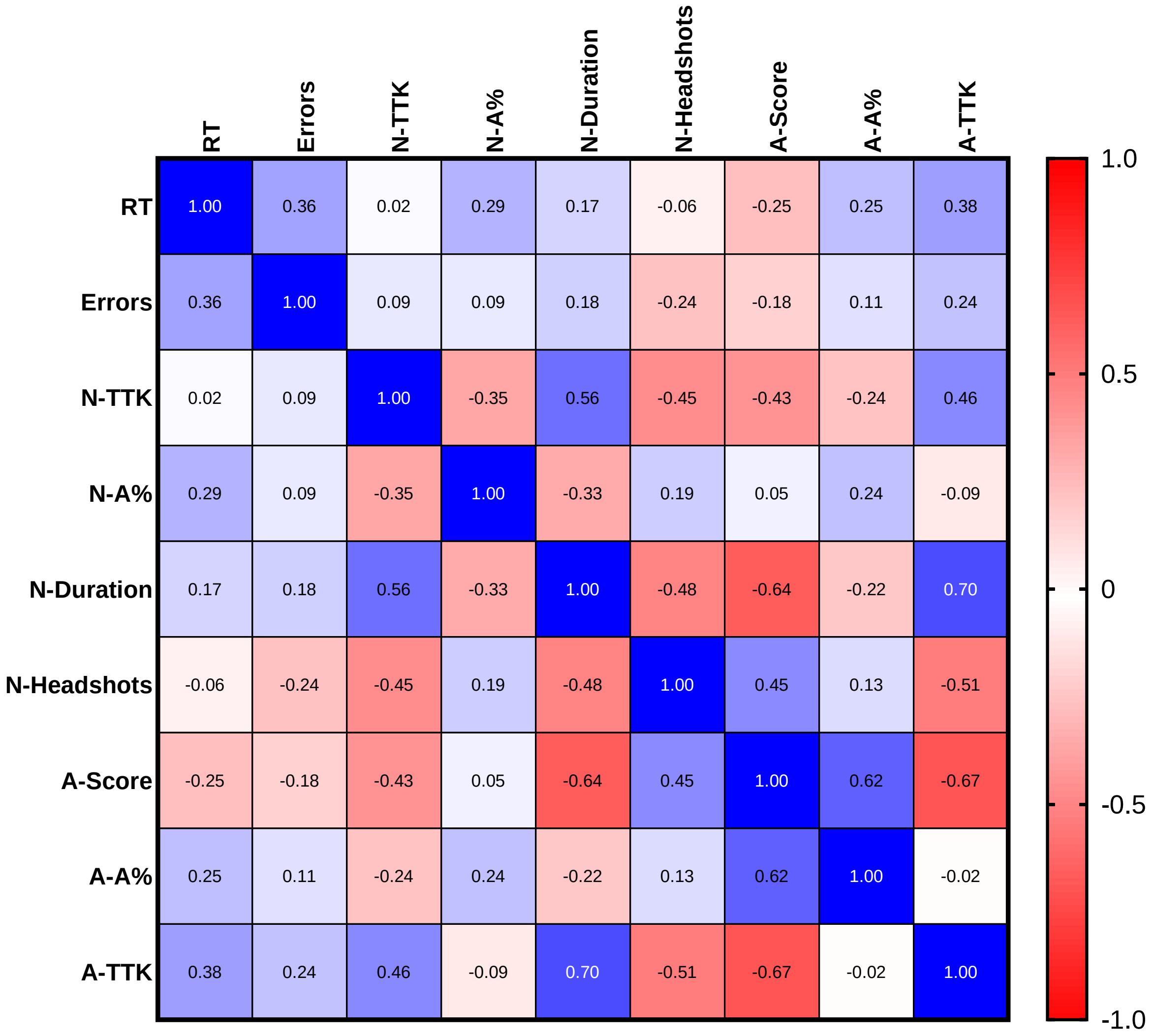
After data is normalized, principal component analysis (PCA) is then applied to the data. PCA is a dimensionality reduction technique used to project multi-dimension data on common axis, called principal components. These components are newly created variables that use a mixture of inputted initial variables to construct new linear combinations. This technique allows for the preservation of information, statistical trends and patterns within the data set. Crucially, principal components are uncorrelated.

After dimensionality reduction, the next step is to identify the presence of clusters within the dataset and test which numbers are the most appropriate to achieve the most effective classification. To do this, an unsupervised machine learning classification technique, k-means clustering has been performed on the transformed dataset. Fundamentally, k-means clustering is used to test for the presence of groups within a dataset. The goal of this clustering algothrim is to assign ‘n’ data items to ‘k’ clusters. It seeks to minimise the following quantity which is the witihin cluster sum of sqaures (the amount of varaition within each cluster, by measuring the distance of each data point in the cluster to the centroid of the cluster beofre summing all of that over the K clusters. K could be any number, it will acheieve clustering if it minimizes the sum of squares.

However, the appropriate number of clusters must be determined based on objective measures of centroid closeness through silhouette analysis. This technique identifies the separation distance between predetermined numbers of clusters resulting from the k-means analysis. When plotted, an objective measure of the how close in data subspace (even transformed data subspace as in this case), of closeness between neighbouring clusters is outputted within a range from [-1, 1]. Because of the precise scores outputted, this technique has been preferred over others such as the ‘elbow method’. Once the appropriate number of clusters are formed, the new dataset can be visualised, patterned based on their cluster.

Results

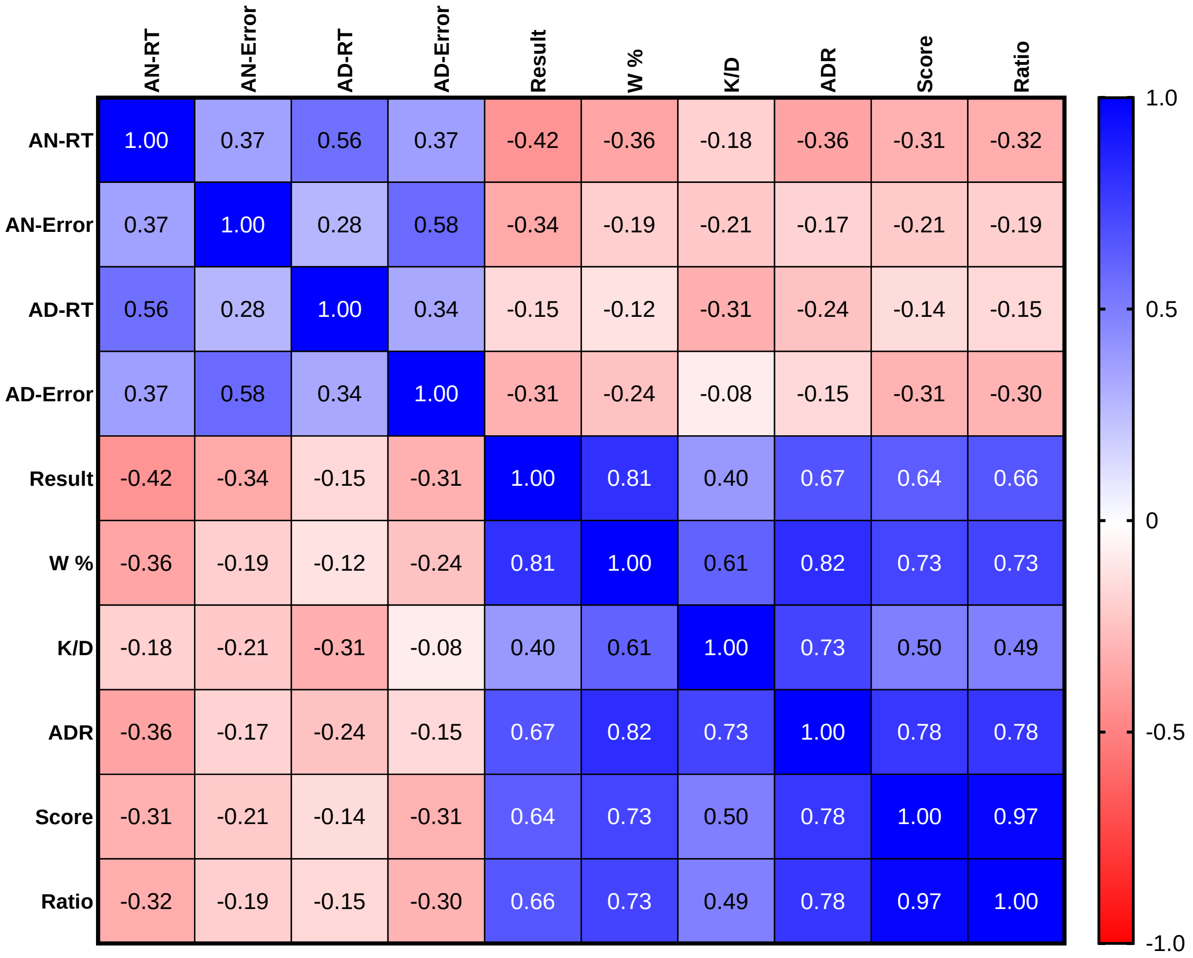
Participants performance data across all tasks contained within the thesis are presented. Correlation analysis is first performed to understand the intrinsic relationships between variables across all.



	RT	Errors	N-TTK	N-A%	N-Duration	N-Headshots	A-Score	A-A%	A-TTK
RT	1.00	0.36	0.02	0.29	0.17	-0.06	-0.25	0.25	0.38
Errors	0.36	1.00	0.09	0.09	0.18	-0.24	-0.18	0.11	0.24
N-TTK	0.02	0.09	1.00	-0.35	0.56	-0.45	-0.43	-0.24	0.46
N-A%	0.29	0.09	-0.35	1.00	-0.33	0.19	0.05	0.24	-0.09
N-Duration	0.17	0.18	0.56	-0.33	1.00	-0.48	-0.64	-0.22	0.70
N-Headshots	-0.06	-0.24	-0.45	0.19	-0.48	1.00	0.45	0.13	-0.51
A-Score	-0.25	-0.18	-0.43	0.05	-0.64	0.45	1.00	0.62	-0.67
A-A%	0.25	0.11	-0.24	0.24	-0.22	0.13	0.62	1.00	-0.02
A-TTK	0.38	0.24	0.46	-0.09	0.70	-0.51	-0.67	-0.02	1.00

Figure 3.1. Correlation analysis of performance variables in study 1. The variables used are across the psychophysics task (Random Flick), the aim-training tasks (AimLabs) and the aim-testing task (NAM1).

The results from the correlation analysis reveal strong relationships between several variables but particularly between the Esports measures. One of the strongest themes in the correlations are shown between time dependent measures e.g. where a high level of performance is shown by temporal metrics. For example, reaction time (RT) in the psychophysics task, significantly correlates with time to kill (TTK). Duration of the gun-phase also significantly correlates with TTK in both the AimLab and NAM1 experiments. The most interesting relationships shown by the correlation analysis of study 1 performance metrics are a significant positive correlation between reaction time and errors, denoting how participants with longer reaction times display increased numbers of errors. Conversely then, the fewest errors are produced by the shortest reaction time, equating to good performance. Secondly, participants with the shortest TTK in NAM1 also displayed a significant negative correlation to accuracy, headshot % and AimLab score, denoting how a faster TTK gives rise to more accurate, better placed shots which yielded a higher score. TTK in AimLab tasks displayed a significant positive relationship to RT, denoting how there is a relationship between slow reaction time and slow TTKs.



	AN-RT	AN-Error	AD-RT	AD-Error	Result	W %	K/D	ADR	Score	Ratio
AN-RT	1.00	0.37	0.56	0.37	-0.42	-0.36	-0.18	-0.36	-0.31	-0.32
AN-Error	0.37	1.00	0.28	0.58	-0.34	-0.19	-0.21	-0.17	-0.21	-0.19
AD-RT	0.56	0.28	1.00	0.34	-0.15	-0.12	-0.31	-0.24	-0.14	-0.15
AD-Error	0.37	0.58	0.34	1.00	-0.31	-0.24	-0.08	-0.15	-0.31	-0.30
Result	-0.42	-0.34	-0.15	-0.31	1.00	0.81	0.40	0.67	0.64	0.66
W %	-0.36	-0.19	-0.12	-0.24	0.81	1.00	0.61	0.82	0.73	0.73
K/D	-0.18	-0.21	-0.31	-0.08	0.40	0.61	1.00	0.73	0.50	0.49
ADR	-0.36	-0.17	-0.24	-0.15	0.67	0.82	0.73	1.00	0.78	0.78
Score	-0.31	-0.21	-0.14	-0.31	0.64	0.73	0.50	0.78	1.00	0.97
Ratio	-0.32	-0.19	-0.15	-0.30	0.66	0.73	0.49	0.78	0.97	1.00

Figure 3.2. Correlation analysis between performance variables in Study 2, containing variables from the psychophysics experiment (Audio delay/normal), the aim-trainer tasks (AimLabs) and Esports competition (CS:GO – Mirage).

As with the previous analysis, the correlational analysis for performance variables in Study 2 display several interesting relationships. In particular, the RT of participants in both psychophysics tasks shows a significant negative correlation with performance variables in the aim-training and Esports competition tasks. That means shorter reaction times in the psychophysics experiment are associated with higher scores, higher K/D ratio and higher ADR, all key indicators of good performance. Furthermore, all Esports related performance metrics, show a significant positive correlation with one another. Ultimately, it is shown here how across both studies, there are strong relationships between performance variables across all experimental tasks.

Importantly, those which have speed as an element, with good performance relating to a shorter time, show significant correlations to key performance variables in Esports related tasks. The present analysis displays rules for good performance, denoted as shorter time is related to higher score.

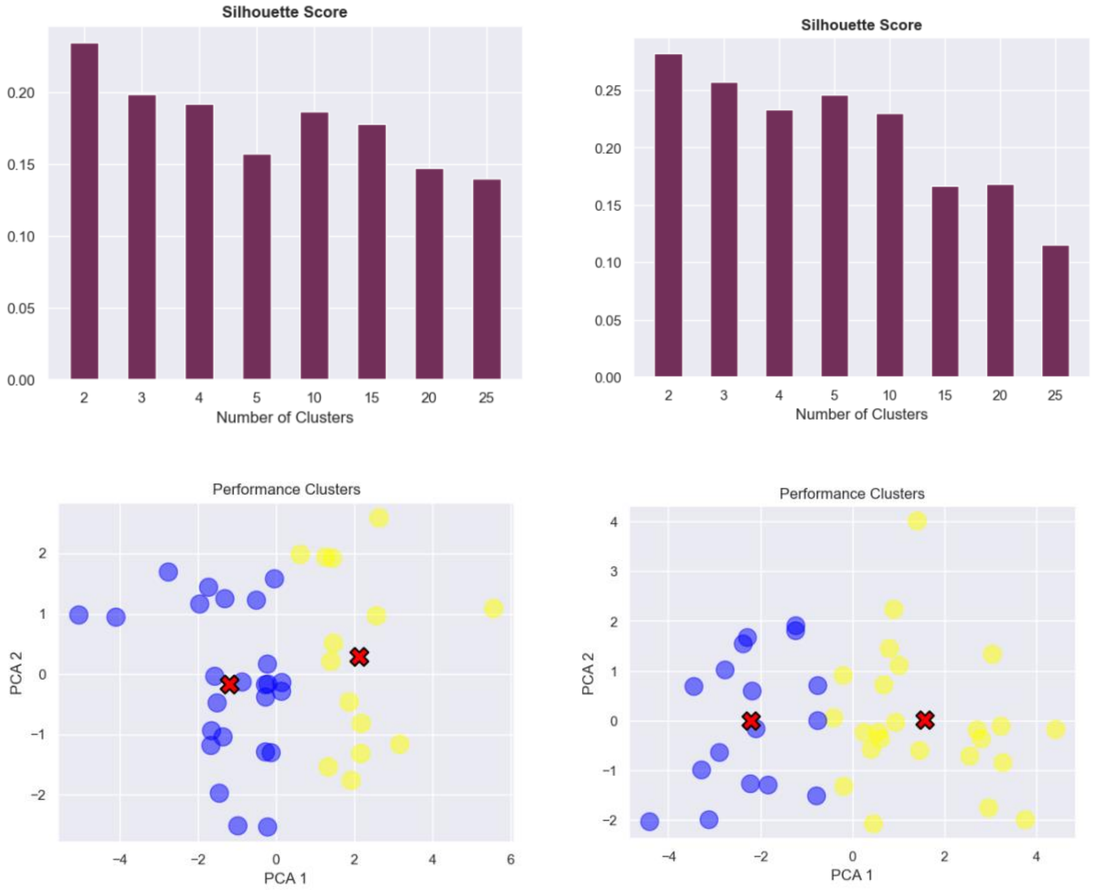


Figure 3.3. Silhouette score of clustering in Study 1 and Study 2 and K-means clustering output

From the silhouette scores above, two clusters are optimal for the datasets provided.

The results of the k-means clustering classification, using two clusters projecting using principal component axis, show the new population. The players have been resorted into their new populations of skilled, those that cluster together in blue, and unskilled, those that are clustering together in yellow. By reducing the dimensions of the diverse performance dataset, and performing clustering on its transformation, it is possible to see that players who perform similarly across all tasks, cluster together.

Discussion

The present thesis seeks to isolate neural correlates of higher performance within a sporting model of Esports. As such it is imperative to separate players into different groups based on their performance level because plotting brain activity against a spectrum of behavioural performance is unmanageable. At first, defining players based on experience within Esports, with experience being a common differentiator of performance, might provide adequate separation. However, there are many issues with self-reporting experience, especially regarding Esports. For example, it is difficult to classify a participant who has a high level of experience with video games, in particular using a mouse and keyboard, but has never played Esports. Alternatively, participants who have played Esports a long time ago, but not recently, offer further difficulties in classification based on self-report. Therefore, an objective data-driven approach is utilized.

In this method, performance data from all experiments is used to test for the presence of clusters, regardless of experience. Players that cluster together, perform most similarly. In this way, two groups were formed based on performance alone and increased separation when based on experience alone. These two new groups contained numerous players who switched from either the inexperienced or experienced group, into the other.

Experience playing video games gives players more of a command over the input modality used to manipulate the players in-game avatar, a potential learning curve for inexperienced players that is not needed for experienced ones. Also, previous experience with Esports, a competitive version of video games, means that cognitively, players understand *virtual* pressure. Especially in FPS Esports, there is a "kill or be killed" aspect that is imperative to good performance. When combining the violence aspect of FPS Esports (e.g. shooting guns, blood, death), previous experience with this selective cognitive pressure should give rise to a higher level of performance. Again, to what extent this will impact performance, especially if there have been many intervening years since then, is currently unknown.

Each task varied in its complexity serving different functions and testing different types of stimuli and movement. In this case, complexity has two forms. First, the complexity of the information that induces the response is increased in its complexity to move closer to that of a full Esport, starting with basic information contained within the psychophysics task. Here, simple shapes, predominately a small black square is used. This visual information has a high contrast to the white background, making the targets very pronounced and easy to identify. The shape itself is also very discriminable from the background due to sharp corners and thick outline. In the aim-training tasks, more vibrant colours are used, in an abstract engaging environment. Targets within the tasks retain their prominence out of the environment only this time using colour as opposed to high contrast. Moving onto the most complex tasks, the information progresses towards being more naturalistic, simulating something closer to the real Esports using character models simulated to look realistic. The second complexity change is the movement being induced. In the psychophysics task, this is just a single movement of varying distances from the central location. Each time a trial is completed, the cursor location is reset to the centre of the screen making each movement discrete. In the other tasks, the cursor location after destroying a target will impact the subsequent target location. This places a greater emphasis on target choice and shot selection by linking all target engagements together.

To acclimatize participants to the experimental set up, a warmup exercise was used. In this exercise participants would have the opportunity to get used to the weight of the electrodes on their head, the chin rest preventing them from moving their head excessively and the distance from the monitor to where the participants sat. This distance was required for the eye-tracker to perform accurately but is at odds with a typical Esports set up. In this set up, experienced players are often extremely close to a monitor, far closer than typical computer work is completed. In many cases, this distance is comically small. There is also the process of adjusting to the use of a mouse and keyboard, something the majority were not used to. For inexperienced players, the only time they had used a mouse and keyboard was for standard computer work. Since all the participants were University students, it is safe to assume that any inexperienced player has spent a significant amount of time using the mouse and keyboard modality, but often not with the selective pressure of accuracy *and* speed. For experienced players who predominately used a controller, this is an opportunity to test out how mouse aiming differs from the requirements of a controller which uses an analogue stick aiming method, transitioning from a manoeuvring a thumb to a hand/arm. A final, and relatively minor consideration is experienced mouse and keyboard players adjusting to the sensitivity. One's sensitivity is very personal. It may differ from game to game or change over time. In many cases, the sensitivity of the mouse was not exactly like the eDPI used by players at home, so adjusting to this was necessary.

By completing the warm-up, all players had the opportunity to familiarize themselves with the environment whilst making a high volume of movements that would be tested throughout the experiment. Furthermore, the exercises reinforced the idea that both speed is a crucial element to performing well, since all tasks had a time-limit associated from trial-to-trial, a concept which is carried throughout the study. Although the correlation analysis displays the intrinsic relationships between performance variables, it does not serve to separate them, only showing the directionality of that relationship. To address this problem, there needs to be a way of separating based on performance and finding two populations that have a large difference, but also intrinsic show similar performance profiles. A first issue is, however, the number of performance metrics used, and how to choose which one. A solution to this, is to use PCA analysis to project multi-dimension data on common axis, through dimensionality reduction.

After performing PCA on the data set, the eigenvalues for each PC and the total variance explained can be found. In figure X we see some interesting dynamics about the dataset that correlate with the behavioural performance. In particular, the largest eigenvalues for the first PC which accounts for 94% of the total variance are largest for TTK measurements (both Aimlab and NAM1 experiments), Score (Aimlab) and the duration (NAM1). Some of the lower measurements are the RT (RF) and both the accuracy metrics (NaM1 and Aimlab). In the second principal component, capturing the remaining 4% variance in the PCA, we find very high eigenvalues for variables which were low previously, and low eigenvalues for variables that were high previously. This shows that, since each PC is orthogonal to each other, they were sensitive to and retaining different information.

Once the data has been transformed to new form, and plotted along the new axis of principal components, it is now possible to perform classification on it. Predominantly, this technique makes the identification of groups possible where there are several predictor variables. To achieve this, machine learning is often employed. Machine learning can either be a supervised process, where a training dataset is used, or an unsupervised process, where a training dataset is not used. In this case, the problem is that experience does not necessarily mean that all players perform better than inexperienced players. As a result, a classification technique could be employed to transform the two populations into those that perform better and those that do not. In other words, a skilled and unskilled population. However, to not bias the result, the previous population group identifier needs to be removed, requiring the technique chosen to be unsupervised.

Conclusion

Finally, the population has been distributed into two groups containing players of similar performance standards. Correlation analysis of all performance variables revealed that there are intrinsic relationships that dictate performance. A particularly strong highlight is how there is a significant negative relationship between time elements and impact, determined as score, accuracy, or damage. This shows how high performance within both aiming tests and Esports competition, is achieved by fast, accurate responses in aiming movements.

To probe whether experienced players perform better, classification was applied to the un-grouped data. PCA was applied to all the performance metrics, achieving dimensionality reduction, and re-projecting the data along a 2-dimensional axis of principal components, retaining information and capturing variance derived from the data. Through silhouette analysis, the optimal number of clusters was determined to be 2, separating the data maximally. Finally, the data groups were re-classified using k-means clustering to attribute the data items, to the optimal two clusters. Intrinsically, the data items within these clusters contain participants whose performance is most similar throughout the data set, but also producing maximum separation to the other cluster. As such, two new population groups are determined which increase the different in average performance from the original population. Due to the number of players in either category switching, it cannot be said that experience faithfully increases performance, due to the presence of inexperienced players displaying similar performance levels. Now though, two distinct performance groups appear with one performing significantly better than the other. From here on, this group will now be referred to as Skilled players and the other unskilled players. The increase in overall performance difference in the newly termed skilled players over the unskilled players, provides a more representative population to elucidate neural mechanisms of high performance as opposed to probing neural correlates of sporting experience.

Chapter 4

Introduction

Understanding how brain activity relates to performing high-skill motor tasks is fundamental to developing better training and development strategies. Such is the scope of sport science that it is now possible to co-register eye-tracking and brain activity with ecologically valid performance of the sport, to identify how brains of high skilled players operate differently to low skilled players. A focus of research in this area has been the use of eye-tracking to probe visual search and fixation behaviours during sporting competition (Kredel et al., 2017). Whilst it was thought that eye-tracking would lead to physical improvement, it has been found that an athlete's cognitive performance and mental state could be interpreted through tracking of eye movements (Moran et al., 2018). A particular focus is understanding the relevant eye-movement strategies employed by elite versus novice players of a particular sport (Hayhoe et al., 2012; Mann et al., 2013. In Esports literature, it has been demonstrated that playing video games leads to significant visual attentional processing changes (Bavalier et al., 2012) and eye-movement performance differences (Mack and Ilg, 2014).

A fruitful avenue of research methodology in cognitive electrophysiology research are visuomotor performance tests. A key cognitive mechanism behind high performance within a visuomotor task is visual perception. Detecting the stimulus is the first step in responding to it. Current research has identified several neural correlates associated with visual perception and discrimination performance, in both the time and frequency domains. Interestingly, sources of evidence centre around two different phases of the response depending on the domain the brain activity is processed in.

Within time domain research using event related potentials (ERPs), a common robust substrate for early stage visually processing is p100, a positive potential detected in occipital sensors 100ms after a visual stimulus onset. It is implicated in target-orientated visual processing (Desmedt and Robertson 1977) and differs in amplitude depending on stimulus location in the visual field (Saba et al., 2023) but stable across either eye (Shors et al., 1986). P100s are implicated in more complex cognitive processes such as face detection (Herrmann et al., 2005, Liu et al., 2013) and sustained attention (Di Russo and Spinelli, 1999).

In athletes, several differences in p100 amplitudes have been found. Greater amplitudes elicited by target than non-target condition in the skilled athlete's group (Sanchez-Lopez et al., 2016). However, several studies have reported reduction in early-stage visual processing ERP components. For example, lower amplitudes have been detected in volleyball and tennis players, rowers, and boxers (Lesiakowski et al., 2017; Shangguan and Che, 2018). However, signal conductivity denoted through p100 peak latency, is reduced in experienced baseball players (Yamashiro et al., 2013) and through extensive volleyball training (Zwierko et al., 2014). These shorter latency ERP components were correlated with reduced reaction time (Yamashiro et al., 2013). As such, p100 is a key visual processing component that shows modulation based on sporting experience or expertise and displays a relationship to behavioural performance measures, implicit in sport.

In the time domain – how voltage changes over time – a major focus in visual perception research, implicit in visuomotor task performance, is a late-stage event related potential (ERP) component originating in occipital parietal regions called p300. As is denoted by the naming convention, p300 refers to a positive ERP component 300ms after stimulus onset therefore it is a post-stimulus component. Although commonly used in auditory oddball paradigms (Lindín et al., 2004), p300 amplitudes have been found to predict visual perception performance (Eimer and Mazza, 2005 ; Salti et al., 2012; Rutiku et al., 2015), an effect that is abolished through visual blurring of targets (Heinrich et al., 2010). Source analysis reveals that the increase in p300 amplitude originates in occipital-parietal sensors (Bablioni et al. 2006). Rare oddball stimuli significantly increase this response (Bernat et al., 2001) but repeated stimuli habituate it (Rayden and Polisch, 1998). A variety of sources position p300 as a manifestation of conscious access, not simply visual perception, and contains signalling to report task-relevant stimuli (Pitts et al., 2014; Mashour et al., 2020). In this way, p300 can be seen as a reflection of the demand for attentional resource allocation in response to sensory stimuli (Gray et al., 2004). As such, it is an incredibly important mechanism for visuomotor response.

The other key focus in cognitive electrophysiology of visual perception is pre-stimulus alpha power. A wide range of research strongly implies that visual detection performance is intrinsically linked to pre-stimulus alpha power through an inverse relationship (Benwell et al., 2017; 2022). Specifically, the ability to discriminate the presence of a visual stimulus decreases with alpha power (Van Dijk et al., 2008) with this effect being present most strongly at the highest intensities of visual stimulus (Chaumon and Busch, 2014). However, whilst pre-stimulus alpha predicts perceptual awareness, it may not predict visual sensitivity (Benwell et al., 2017). Importantly, low alpha power was also associated with significantly higher ERP amplitudes (Iemi et al., 2017). This suggests that short-term changes in time domain brain activity post stimulus are linked to frequency domain power differences. Research using dual visual phenomena, which induces high inter-trial perception variability, has postulated that the associated power decrease in pre stimulus alpha is resulting from enhanced global visual system excitability (Lange et al., 2013). Individual variability in posterior alpha and illusionary threshold is another consideration, discovered through transcranial magnetic stimulation-induced visual percepts (Romei et al., 2008). This suggests that although conceptually reduced alpha power’s relationship to perceptual performance appears stable, individual differences modulate perceptual thresholds.

As such, posterior alpha power modulates gain in the visual system and potentially reflects the accumulation of evidence (Kloosterman et al., 2019), a key process in decision-making. Through an accumulation of sensory evidence over time, activity increases to a threshold, which, when crossed, triggers a decision output. In this case, visually guided precise movement. This is a key substrate for the differences between a skilled and unskilled population, beyond the movement dynamics itself, but occurring in the pre-movement processing stage. In this way, a more broader decision criterion could be facilitated by lower alpha power (Limbach and Corballis, 2016) reducing the time to hit threshold, manifesting a faster reaction time.

Within visuomotor tasks, beta power (13-30Hz) is another important frequency band. Two key periods are heavily implicated in performance of complex movements, those being Movement-Related Beta Desynchronization (MRBD) and Post-Movement Beta Rebound (PMBR). MRBD is a distinct pattern of beta oscillatory power decrease (or desynchronisation) relative to a baseline period and reflects movement preparation, initiation or execution (Zhang et al., 2008).

MRBD as well as resting beta power, has been found to be highly reliable after motor-training interventions across participants, across sessions in both sensorimotor cortices (Espenhahn et al., 2017). There is a significant relationship between MRBD and resting beta power in primary motor areas in addition to MRBD magnitude and movement duration (Heinrichs-Graham and Wilson, 2015). This effect may also reflect performance since when reaching, those movements that were preceded by a greater reduction in beta power, exhibited significantly faster movement onset times (Khanna and Carmena, 2017). MRBD is sensitive to different populations of people, with differences across age, increasing MBRD amplitude and resting beta power (Wilson et al., 2014), increases in desynchronisation in the morning to afternoon period (Wilson et al., 2014) and in Parkinson’s and Stroke patients, where MRBD in motor cortices was found to be significantly reduced compared to control groups (Heinrichs-Graham et al., 2014; Rossiter et al., 2014).The strength of MRBD is also modulated by the type of movement required, such as posture, force and movement duration (Nakayashiki et al., 2014). Reducing beta power pre-movement, a reflection of motor-planning, predicts the subsequent increase in adaptive drive (Darsch et al., 2020). Finally, there is a lateralized MRBD effect where implicated in motor selection (Doyle et al., 2005), however, it is said to be strongest where cues a present, facilitating a reduction in reaction time.

PMBR is a synchronisation event that occurs after a movement has been terminated (Pfurtscheller et al., 1996). It reflects active inhibition of motor areas (Salmelin et al., 1995). The amplitude of PMBR is subject to modulation by several different factors of the movement that has just terminated. Specifically, the type of afferent input (Houdayer et al., 2006) such as the rate of force development and the force magnitude

(Fry et al., 2016). It is generated in the motor cortex and was strongest contralateral to the side of movement (Jurkiewicz et al., 2006). However, since beta synchronization is present regardless of whether a movement was active or passive (Cassim et al., 2001) or if the movement was suppressed or imagined (Solis-Escalante et al., 2012). Therefore, PMBR might signal more than simply movement termination and has become associated with somatosensory processing of the previous movement, functioning as a cognitive check. This is supported by findings from Tan et al (2016) who found a strong relationship between PMBR and confidence that a movement prediction was correct. A potentially stronger link to PMBR and cognition is the finding that synchronisation decreases post erroneous movements, relative to error size (Tan et al., 2014). As such, PMBR is modulated by motor learning and reflects salience processing, implicated in goal-directed movements (Torrecillos et al., 2015; Korka et al., 2023).

To isolate the contributions of the visual system to the movements of skilled and unskilled Esports players, a visuomotor performance test is proposed. This test perfectly recreates the flicking movement by pulling participants around the screen and is a single action task to reduce variables. Within Esports, flicking is a regarded as rapid reflexive movement that changes cursor location to static targets quickly. It is an incredibly important movement within Esports, fundamental to FPS performance. Flicking maps perfectly onto saccades in terms of the movement execution. The rapid alteration to gaze location in a target directed manner, emanates the concept behind flicking which rapidly alters a player's crosshair – central point of the screen and indicator of aim direction. The mechanics of the movement area create in such a way that they are the same as you would expect in Esports, the only difference being the sensory information used. In Esports this information would be incredibly complex with bright colours, intricate shapes, that be attempting to be lifelike such as in historical war games (such as call of duty or counterstrike), or very much not in games using more unrealistic visuals (such as Valorant and Overwatch). In this experiment, the visual information is simplified as much as possible so that the recorded neural activity is simplified compared to Esports and traditional sports in general, and that the neural dynamics are related to a single, stationary object, not anything with movement, or anything that needs to be processed in a higher-order cognitive way. This experiment therefore seeks to address how visual information is used to guide a fast and precise movement by isolate time and frequency domain activity both pre and post stimulus onset.

The main aim of this study is to create a simple visuomotor task that tests a fundamental movement in Esports. It is hypothesized that skilled players will execute this movement better due to two key neural correlates. Firstly, skilled players will display an enhanced visual response to the stimulus onset, responding stronger to it and eliciting faster visual processing. Increased ERP component amplitudes, such as p100/p300 and decreased pre-stimulus alpha power, are expected to increase visual perception of the stimulus. This in turn, facilitates a higher performance. Secondly, that skilled players will display an enhanced motor response when executing the movement, coordinated by increased theta and beta power.

Methods

Participants

37 participants (15 Male, 12 Female) took part in the experiment, 36 of which were students at University of Birmingham, one was a Marine (UK Armed Forces). Of the participants, 19 were classified as Skilled players and 18 were classified as unskilled players based on the methods described in the previous chapter. Briefly, after reporting Esports playing time based on a self-report questionnaire, populations were determined based off Esports experience only. Players who played video-games, whichever input modality, but not Esports were determined to be inexperienced. After completing various Esports and psychophysics tasks, their performance on these tasks was used to perform k-means clustering and identify clusters of similarly performing player groups. Silhouette scores determined that two clusters were optimal, and players were classified based on their cluster. Their previous experience was not included as part of the classification process. All participants were right-handed, didn’t wear glasses and had no history of neurological disorders. Crucially, all participants reported some experience with video-games.

Experimental Procedure

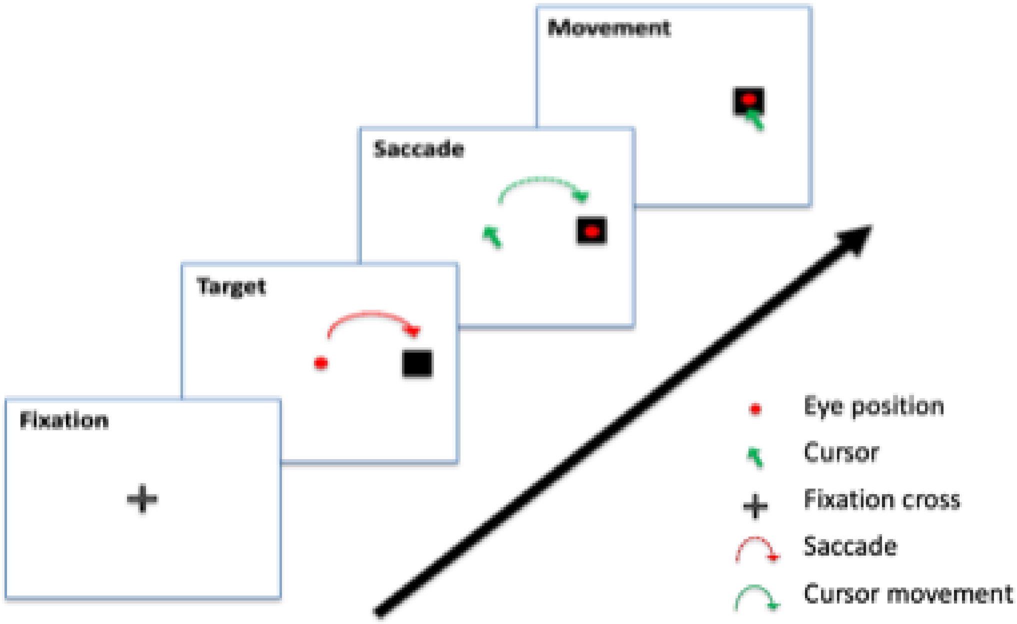


Figure 4.1. Experimental design for the experiment displaying the fixation period, stimulus onset, eye movement and cursor movement.

All psychophysics experiments were created using SR Research experiment builder to accurately co-register with the eye-tracker and stimulus pc. In each experiment, a fixation cross began the trial by being present for 1000ms localizing eye fixation to the centre of the screen. After the fixation period was over, the mouse location was set to the centre of the screen and the response target, a visual stimulus, would appear on the screen. The target was a small black square, projected on a white background to maximise contrast. Participants would then have 1000ms after stimulus onset to move the mouse to the target and click on it, with only clicks registering within the target boundary being registered. The reaction time, calculated from stimulus onset to a successful click, was recorded, as well as the number of failed trials, reported as errors. If the trial was successful, a blank screen was present for 500ms. If the trial was failed because a successful click wasn't registered within the 1000ms this would be recorded as an error and a message reading "FAILURE, MOVE FASTER!" would appear on the screen in bold red lettering. After 500ms of this message being present, another trial would begin, denoted by the fixation cross reappearance.

Before each block, participants would receive instructions and complete eye-tracker calibration steps. There were three different blocks, with each block using a different target size decreasing by 10 pixels squared each block (30x30 pixels to 10x10 pixels). All targets remained the same colour throughout and occurred at a set number of locations (20 left and 20 right, 10 centre).

Eye-Tracking

Eye-movements were recorded using an Eyelink 1000 plus (SR Research), with eye-tracking calibration steps performed before all experimental blocks before the delivery of tasks instructions. To quantify eye-movements during the study, SR research's data analysis tool, Data Viewer was used. This facilitated the identification of saccade, fixations, and trial reports. Due to the experimental coding being in another data package from SR research, all trials ported over contained the necessary trial condition information such as the target size, location, and calibration reports. To identify eye-movements exclusively during the trial period, a reaction time variable could be initialized which marked the moment of stimulus onset, detected by the time the host pc received the stimulus onset trigger (the same trigger received by the EEG amplifier) to the moment it received the outcome trigger, either success or failure. As such, only eye-movement event-locked to the stimulus onset were included in analysis. Saccades below 1 degree were excluded from analysis.

EEG recording and analysis

The data was acquired using a 64-channel EEG (BioSemi) and processed using MNE – python toolbox, as described in Chapter 2. The data was subjected to a number of pre-processing and processing steps as outline in the methods chapter. Briefly, noisy sensors were first removed and interpolated by RANSAC algorithm. Then the data was downsampled to 200hz to reduce computation time. After downsampling, events were marked depending on population (skilled or unskilled), event (stimulus onset or response) and outcome (success or failure). From here the data was passed through the AutoReject algorithm to reconstruct and drop extremely noisy epochs before being passed to the ICA algorithm which allowed for artefact detection and removal. Then the data was passed for a final time to AutoReject to reconstruct any remaining noisy epochs and drop any that still didn't pass the threshold (a lower threshold than the first AutoReject pass). At this point, the now clean data was filtered from 1-30Hz (high and low-pass) and average referenced. Epochs from this position could finally be averaged together to form evoked objects, or grand average ERPs, per population, event, and outcome.

Time-domain analysis

To identify the visual stimulus related component of ERPs, occipital parietal electrodes were grouped and plotted as ERPs, event locked to stimulus onset, depending on the outcome. Stimulus onset events that were followed by events of interest were defined using the function 'define_target_events' allowing for new events to be created if a target event follows the original event, within a certain time-window. This allowed stimulus onset events during success trials, and stimulus onset during failure trials, to be identified separately and compared.

Frequency-domain analysis

With clean and pre-processed data, Morlet waveform analysis was applied to frequencies of interest. In this experiment, the frequency ranges used were Theta (4-7Hz), Alpha (8-12Hz), Low Beta (13-21Hz) and High Beta (22-30Hz), calculating individual frequencies in steps of 1Hz. To define the number of cycles, the frequency range was divided by 2 and fast Fourier transform was applied. Power for each frequency was then averaged.

Statistical analysis

Statistical analysis was conducted differently depending on the type of data, behavioural data and outputted measurements of time/frequency elements, were analysed using Prism (GraphPad). Examples of this are behavioural performance, eye-tracking, ERP measurements and power estimates. Statical analysis of complex time/frequency elements were analysed using MNE-Python. To establish a statistical relationship between time/frequency elements, outcome, and population, peak measurements of grand averages and averaged power estimates were made. These measurements were then statistically analysed using a 2-way ANOVA comparing Population x Outcome, corrected for multiple comparisons using Tukey's post-hoc test. 1-D cluster-based permutation statistics were calculated for difference waves, testing deviation from zero. An F-value threshold of 6 was used to determine a significant cluster.

Source localization

To achieve source localization several different techniques were used to estimate both activation and power changes in the source space. To compute all solutions, a forward model was create using the standard template MRI subject fsaverage (FreeSurfer). Using Dynamics Imaging of Coherent Sources (DICSs), a volumetric forward model was created. To do this the template MRI was used to construct boundary element model (BEM) using a three-shell model (brain, inner and outer, skull).

To calculate source activations a linear minimum-norm inverse method (eLORETA) was computed and applied using a regularized noise covariance matrix. From here, the inverse solution can be calculated, and source time courses obtained. To calculate event-related source power changes the DICS method was used with the volumetric forward model. Cross-spectral density was calculated for each frequency band using morlet waveform transformations using a baseline covariance matrix (pre-trial) and an active covariance matrix (during trial), in this case, the baseline was set 1.5-1s prior to the pre-stimulus fixation cross period, where a blank screen was present after the termination of the outcome message.

Results

Behavioural Performance and Eye-Tracking

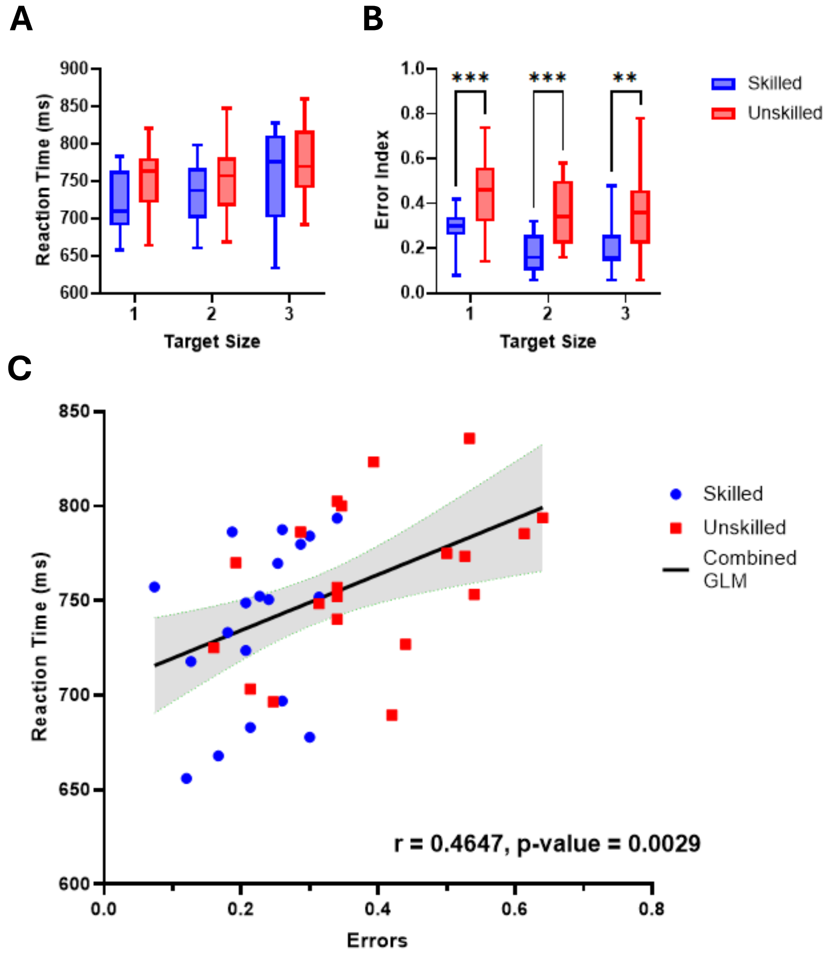


Figure 4.2. Behavioural results from Random Flick psychophysics task depending on target sizes (1 = large, 2 = medium, 3=large) with skilled players in blue and unskilled players in red. Upper and lower range are shown and box size represents standard deviation. A) Box plot of reaction time depending on target size. B) Box plot showing error index depending on target size. C) Correlation between reaction time and error index with general linear model plotted in black. Statistical analysis in box plots is 2-way ANOVA corrected for multiple comparisons using Tukey with significant comparisons marked (* = 0.01, ** = 0.001, *** = 0.0001).

The behavioural results indicate there is not a significant interaction between target size and population with reaction time (F(2,72) = 0.3235, p = 0.7247), however there is a significant interaction between target size and population with error index (F(2, 72) = 9.457, p = 0.0259). Skilled players displayed faster average reaction times (F (2, 36) = 19.76, p=0.0911) to unskilled players, although the lack of significant interaction doesn’t justify post-hoc comparisons. The number of failed trials, referred to as errors, was used to create an error index, the likelihood of a player to make an error, are significantly different in skilled players compared to unskilled players (F (2, 36) = 19.76, p = <0.0001). Tukey’s multiple comparison post-hoc test indicated significant differences at all target sizes, from 1 to 3 (p = 0.0005, p = 0.0002, p = 0.0016, respectively). Skilled players made significantly fewer errors and thus had a significantly small error index than unskilled players across all target sizes. In the correlation analysis there is a significant correlation between the two performance variables across the combined population (p-value = 0.0029). There is a strong positive relationship between reaction time and error index (r = 0.4647, p = 0.0029). Skilled players show a significantly better behavioural performance by showing a faster reaction time and fewer errors, two variables that are strongly correlated.

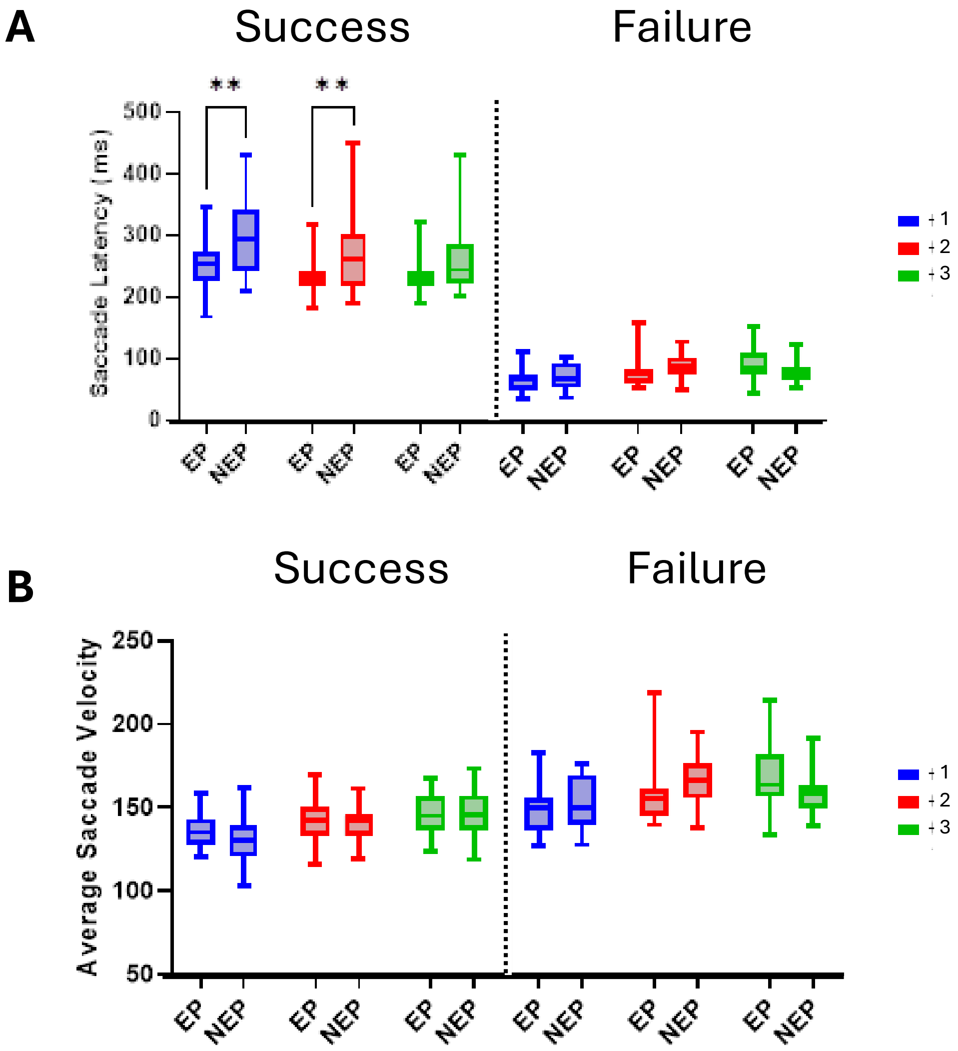


Figure 4.3. Eye tracking performance across Random Flick experiment. A) Saccade Latency in successful and unsuccessful trials across different target sizes. B) Average saccade velocity in successful and unsuccessful trials across different target sizes.

Eye-tracking results indicate a difference in execution between skilled and unskilled players (EP and NEP). There is a significant interaction between Population and Target size in the Saccade latency (F(5, 216) = 3.045, p = 0.0112. There is also a significant in population difference (F(1, 216) = 15.24, p = 0.0001) and there is a significant difference across all target sizes (F(5, 216) = 88.31, p < 0.0001). When correcting for multiple comparisons there are significant differences in saccade latencies across with p-values of 0.0032, 0.0059, 0.0394 for sizes 1, 2, 3 respectively. There are no significant differences between saccade latency in failed trials. There is not a significant interaction between population and Target size in average saccade velocity (F(5, 216) = 1.824, p = 0.1094). There is not a significant difference across populations (F(1, 216) = 0.2281, p = 0.6334). There is a significant difference across outcomes/target size (F(5, 216) = 23.47, p<0.0001). The lack of a significant interaction doesn't justify

Time-Domain Analysis

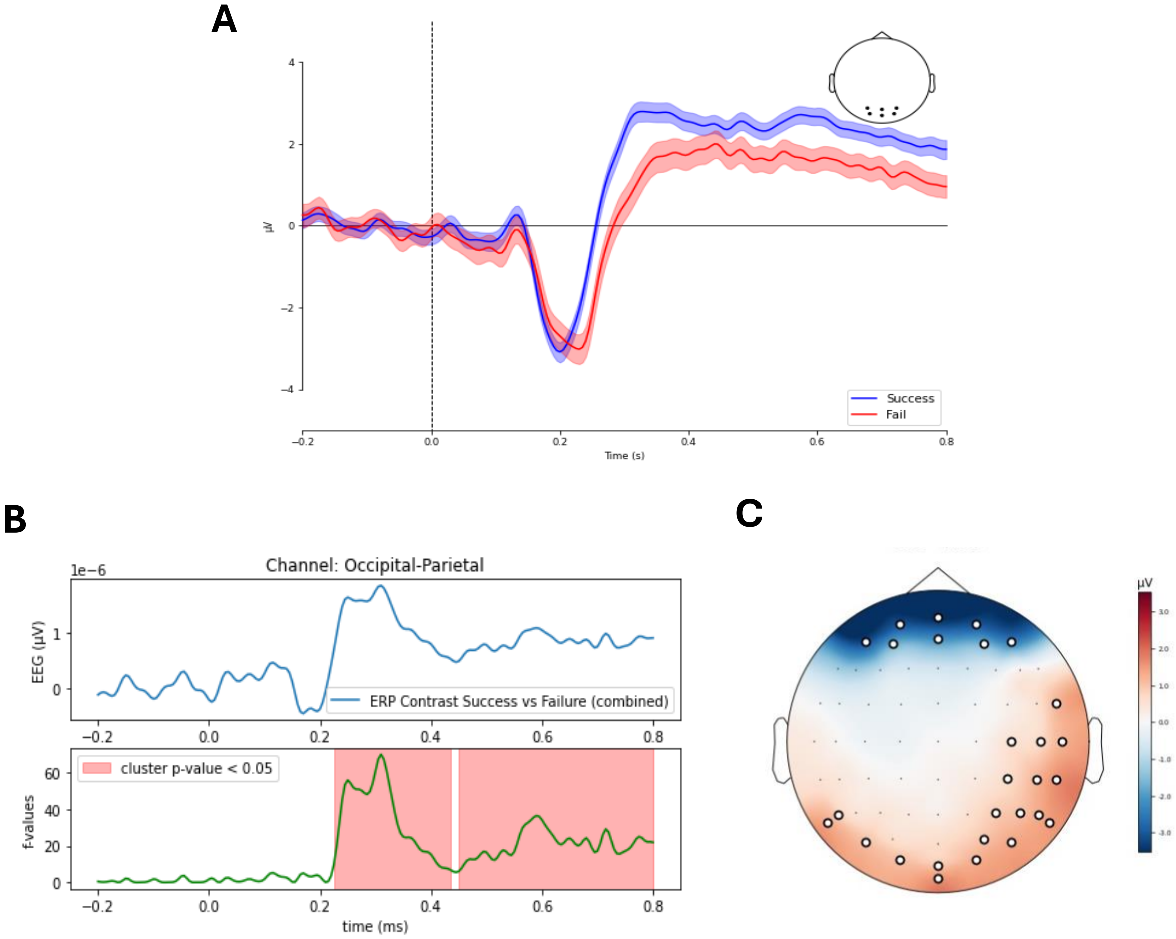


Figure 4.4. Grand average ERPs after stimulus onset in skilled and unskilled players preceding a success or failed response. A) Grand average ERPs comparing the different waveforms of skilled and unskilled players then comparing the difference between outcomes when populations are combined. 2-way ANOVA results are plotted comparing Population x Outcome and corrected for multiple comparisons using Tukey's post-hoc test. B) Grand average difference wave ERPs between skilled players, unskilled players and between outcomes across populations, corrected for multiple comparisons using cluster permutation test. C) Permutation T-test of sensor data 300ms after stimulus onset projecting a Skilled minus Unskilled difference wave onto a head model.

The time domain results display a statistical interaction between voltage change during the trial dependent on both population and outcome. 2-way ANOVA results report a statically significant difference between outcome (p=0.0206) and a population (0.0516), When corrected for multiple comparisons only skilled players show a statistically significant difference between outcomes. Therefore, although there is a trend of differences between population and outcome, only skilled players show a significant difference in p300 amplitude between success and failure outcomes, there is a significant difference in VAN latency (p-value 0.0443). The difference wave plots and subsequent 1-D cluster permutation statistics, display a significant difference period in skilled vs unskilled players between 100-150ms after stimulus onset in successful trials, but no significant difference periods afterwards, although a post threshold, sub significant, peak occurs at 400-450ms. In the failure trials, an above-threshold, but insignificant peak occurs between 100-150ms after stimulus onset, but no significant difference are detected comparing skilled and unskilled players. Finally, there is an extended period of significant difference in a combined population, comparing success and failure trials. The onset of this difference begins ~200ms after stimulus onset and extends to the termination of the trial. The occipital-parietal sensors response significantly differs in the early response elements preceding a successful or unsuccessful trial, with those differences being most significant in skilled players.

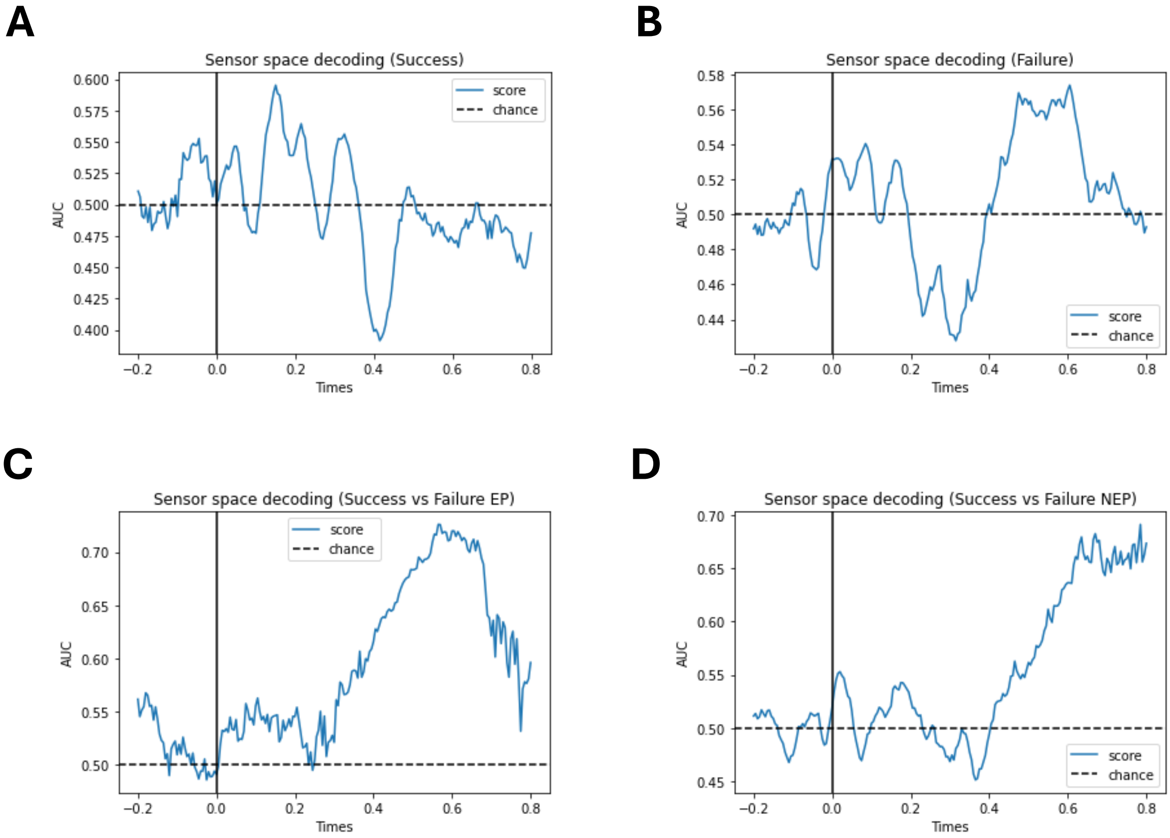


Figure 4.5. AUC scores from decoding MVPA between populations and outcome. A) AUC scores comparing skilled and unskilled players in successful trials. B) AUC scores comparing skilled and unskilled players during failed outcomes. C) AUC scores comparing success and failure outcomes in skilled players. D) AUC scores comparing success and failure outcomes in unskilled players. Chance line is placed at 0.5.

The decoding MVPA on voltage change over time displays how discriminable two states are from one another. In figure 4, peak decoding performance, denoted by highest AUC scores is comparing outcomes within populations. The highest best decoding classifier performance was achieved discriminating between success and failure in skilled players, peaking 550-600ms. Although similar, the decoding classifier performance peaked in unskilled players between 600-800ms. Comparing within outcomes, across populations, decoding classifier performance between skilled and unskilled players in successful outcomes occurred 100-200ms after stimulus onset, whereas peak classifier performance in failure outcomes occurred between 400-600ms after stimulus onset. Taken together, there is a large difference between the brain activity across the whole brain between outcomes, with this being most pronounced in the latter stages of the trial and in skilled players. Within outcomes, classification is at its peak in early stages of successful outcomes and latter stages in failed outcomes.

Frequency-Domain Analysis

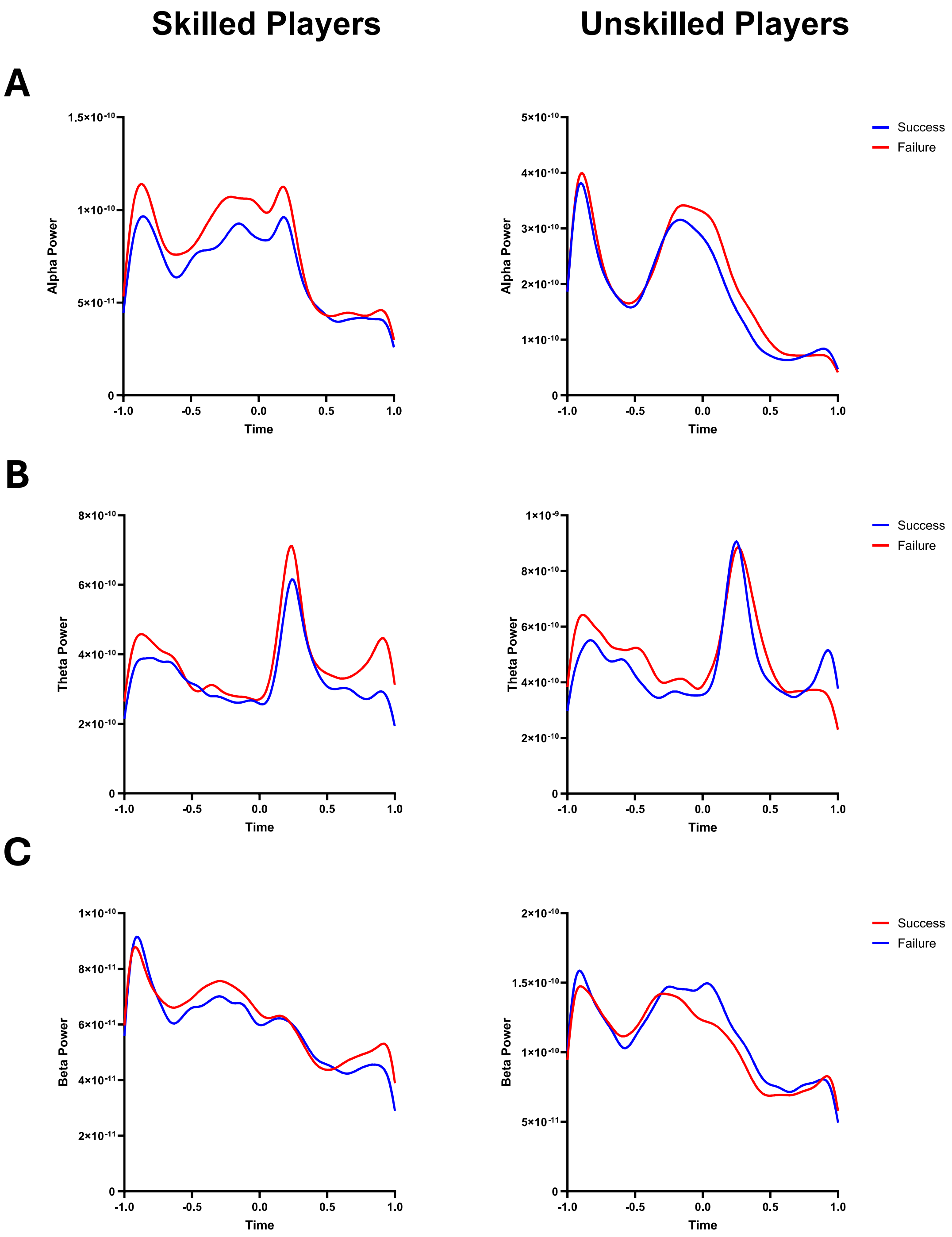


Figure 4.6. Alpha and Theta power changes over the pre-stimulus, and post-stimulus onset periods. A) Alpha power changes in occipital-parietal (Oz, O1, O2, POz, PO3, PO4) electrodes across skilled and unskilled players. B) Theta power changes in frontal-central (Fz, F1, F2, FCz, FC1, FC2) electrodes across

skilled and unskilled players. C) Beta power changes in midline (Cz, C1, C2, C3, C4) electrodes across skilled and unskilled players. Success trials are plotted in blue and failure trials are plotted in red.

The oscillatory power changes in the alpha and theta frequency band occurring during the trial period display different relationships between success and failure trials. In success trials, there is lower pre-stimulus alpha power across both populations. Both populations show a spike of alpha power directly after the fixation cross onsets but drop in power quickly and markedly. In skilled players, alpha power gradually builds until stimulus onset (time 0) followed by another small spike, before dropping. In unskilled players, a different time course shape is observed where a steep rise and fall of alpha power occurs, rising sharply 500ms before stimulus onset, and falling quickly afterwards. In skilled players there is consistently lower alpha power until 2-300ms after stimulus onset. In unskilled players, alpha power is also lower in successful trials, but this difference only occurs 2-300ms before stimulus onset, continuing as alpha power drops with the difference ending about 500ms after stimulus onset. With theta power, there appears to be a large spike occurring in frontal central electrodes in both populations, drastically increasing theta power after stimulus onset, lasting for around 500ms. In skilled players, there is a large difference in theta power between success and failure trials, this difference is not present in unskilled players.

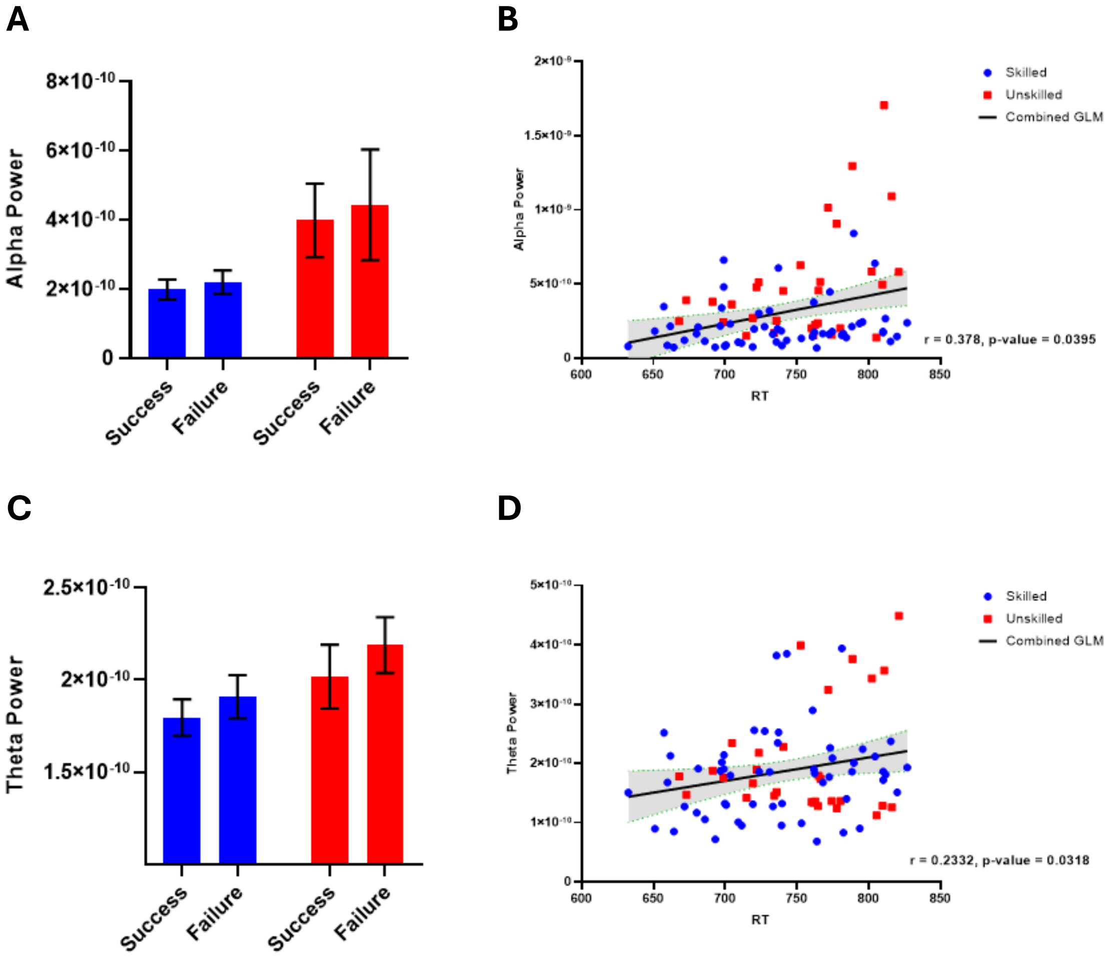


Figure 4.7. Neural oscillations during visuomotor task performance. A) Pre-stimulus alpha power during successful and failed trials with its correlation to reaction time. B) Correlation between pre-stimulus alpha power and reaction time during successful trials. C) Post-stimulus theta power during successful and failed trials with its correlation to reaction time. D) Correlation between post-stimulus theta power and reaction time in successful trials. All Skilled players are plotted in blue, all unskilled players plotted in red.

The interaction between Outcome and Population for post-stimulus theta power is not significant (F(1,83) = 1.413, p = 0.2389). Alpha power in the pre-stimulus period is significantly different between skilled and unskilled players (F (2, 66) = 24.43, p = <0.0001) and significantly differs between successful and failed trials (F (1, 66) = 10.91, p = 0.0016). Due to the lack of significant interaction, post-hoc analysis is not justified. The interaction between Outcome and Population for post-stimulus theta power is not significant (F(1,83) = 0.4955, p = 0.4687). Theta power was significantly different across successful and failed trials (F (1, 83) = 11.43, p = 0.0011) but not when comparing skilled and unskilled players (F (1, 83) = 1.833, p = =0.1794). Due to the lack of significant interaction, post-hoc analysis is not justified. Correlational analysis indicated a significant relationship between pre-stimulus alpha power and reaction time (r = 0.378, p = 0.0395) across all participants and in post-stimulus theta power (r = 0.2332, p = 0.0318). This indicates a strong inverse relationship between pre-stimulus alpha power and post-stimulus theta power with high performance. There is a strong relationship between neural oscillations and performance, displayed by significantly reduced pre-stimulus alpha and significantly reduced post-stimulus theta predicting reaction time.

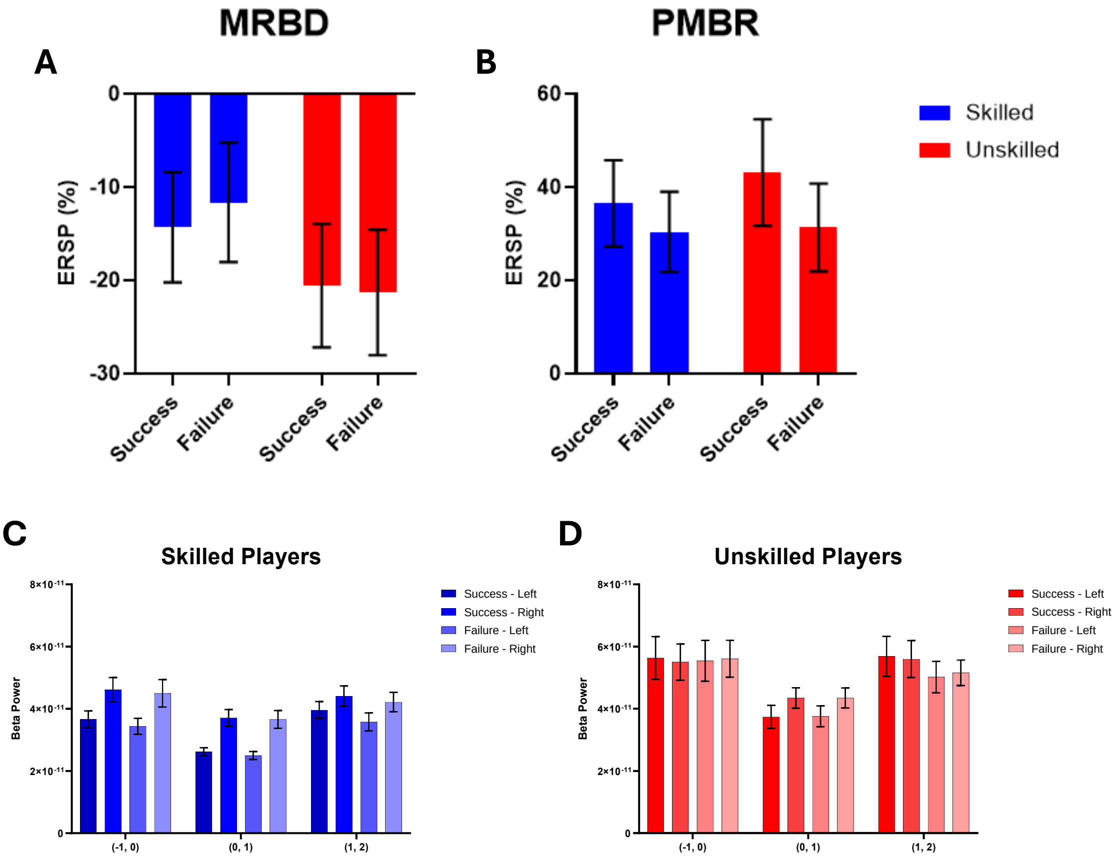


Figure 4.8. Event related beta power changes. A) Movement related beta desynchronisation (MRBD) differences between success and failure trials. B) Post movement beta rebound (PMBR). Beta power lateralisation across different time points occurring during the trial in skilled players (C) and in unskilled players (D). The time points used are pre-movement (-1s to 0s), movement (0s to 1s) and post-movement (1s to 2s), plotting the different between left and right frontal-central sensors across success and failure trials. In A and B, skilled players are plotted in blue, unskilled plotted in red.

Beta power data captures prominent MRBD effects occurring in both skilled and unskilled players. There is no significant interaction between outcome and population for MRBD (F(1, 83) = 1.551, p = 0.2165) or PMBR (F(1, 83) = 0.6655, p = 0.4170). There are also no significant differences in MRBD ERSP between population (F (1, 83) = 2.974, p = 0.0884) or between trial outcomes (F (1, 83) = 0.4954, p = 0.4835). PMBR displayed a significant difference between successful and failed trials across populations (F (1, 83) = 6.463, p = 0.0129) but not between populations (F (1, 83) = 0.3717, p = 0.5437). Since there was no interaction effect across MRBD or PMBR, post-hoc analysis is not justified. There were observed lateralization effects between left and right-side electrodes. In skilled players there was a significant difference between left and right electrode beta power (F (0.7568, 40.87) = 5.423, p = 0.0333) and between successful and failed trials (F (0.7568, 40.87) = 5.423, p = 0.0333), however there was not a significant difference between trial outcome and lateralization (F (0.8610, 46.49) = 3.461, p =0.0745). In unskilled players, there wasn't a significant difference between left and right electrode beta power (F (1, 29) = 0.9790, p =0.3306) or trial outcome (F (1, 29) = 2.409, p =0.1315), or combining trial outcome and lateralization (F (1, 29) = 1.231, p = 0.2764). Overall, there is a greater MRBD across both outcomes in unskilled players. PMBR display greater ERS in successful trials than in unsuccessful. Skilled players display a high-degree of right-sided lateralization that is not present in unskilled players.

Source Space Analysis

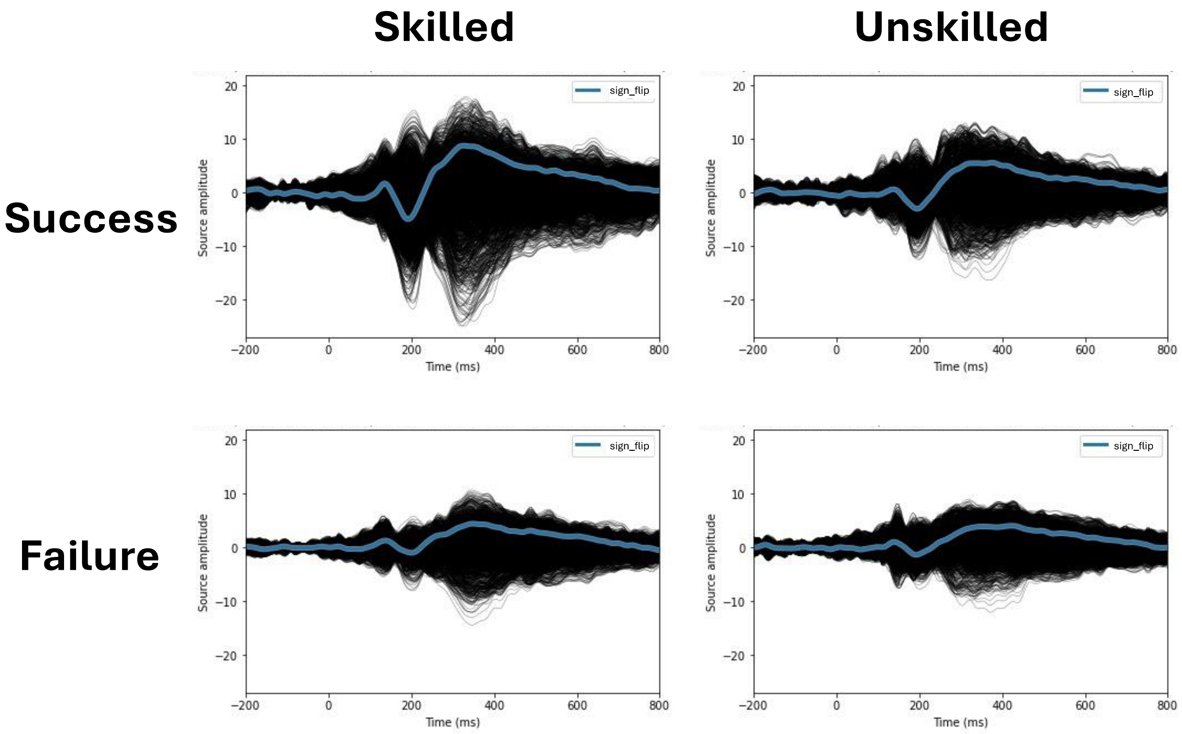


Figure 4.9. dSPM source amplitude differences between population and outcome computed with a sign flip across occipital-parietal labels. A) dSPM source amplitude change over trial period in successful trials of skilled players. B) dSPM source amplitude change over trial period in successful trials of unskilled players. C) dSPM source amplitude change over trial period in failed trials of skilled players. D) dSPM source amplitude change over trial period in failed trials of unskilled players. All panels have single epoch source amplitude plotted, with mean values computed using sign flip overlaid.

The source amplitude changes are plotted to transform sensor space voltage changes to the source space. Within both populations, differences in source amplitude are present between outcome conditions, with a greater amplitude occurring in successful trials occurring 300ms after stimulus onset. The peak source amplitude is higher in skilled players compared to unskilled players; however no detectable differences occur in the failure outcome between populations.

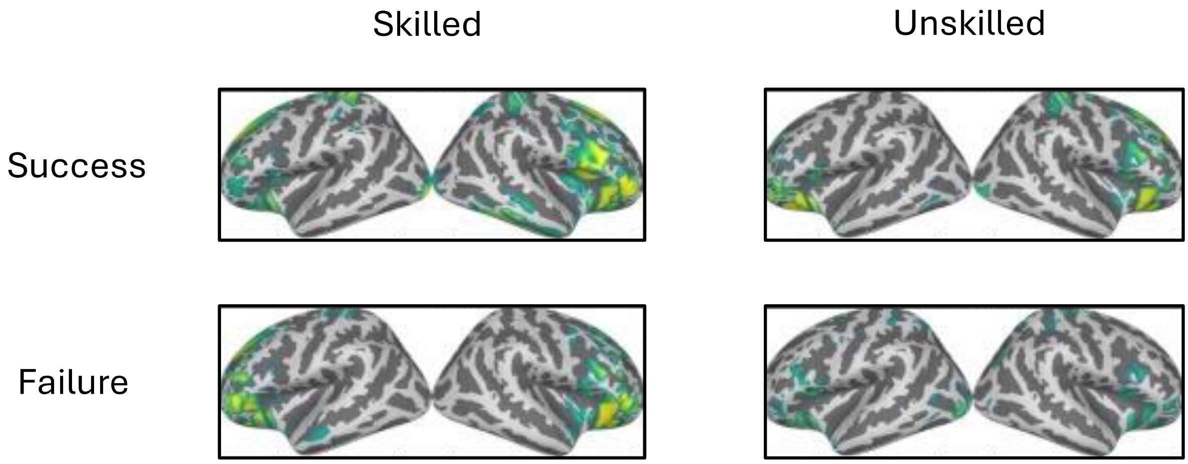


Figure 4.10. eLORETA source localization across 200-500ms period across skilled and unskilled players, during success and failure trials.

Source localization of time-domain activation shows distinct differences between skilled and unskilled players in both successful and failed trials. Skilled players, during successful trials show the most global distribution of activity across several important brain regions, most notably, frontal central regions and parietal regions. Failed trials of skilled players display distinctly less activation in frontal-central regions and little parietal activity. In unskilled players, the difference between successful and failed trials follows a similar pattern with greater activation in successful compared to failed trials. Across all participants, a relative right-sided lateralization in frontal central regions is apparent.

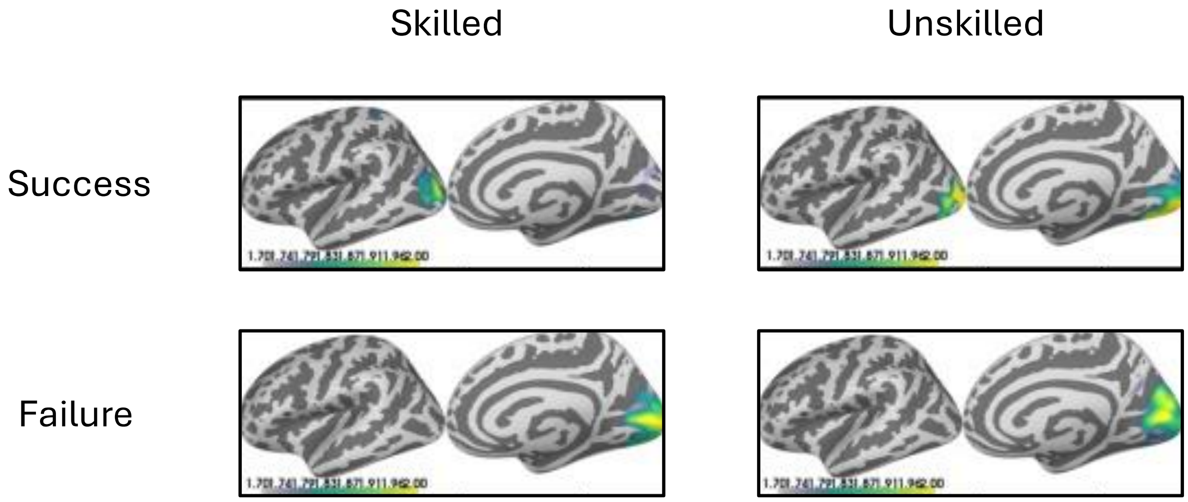


Figure 4.11. Alpha power source localization during the pre-stimulus period using DICS across skilled and unskilled players, during success and failed trials.

Pre-stimulus alpha power is localization to occipital regions of the brain in source space. In skilled players there is a low level of alpha power in successful trials, with higher power in failed trials. In unskilled players, there is greater alpha power localization in both trial outcome conditions, with the highest power occurring in failed trials.

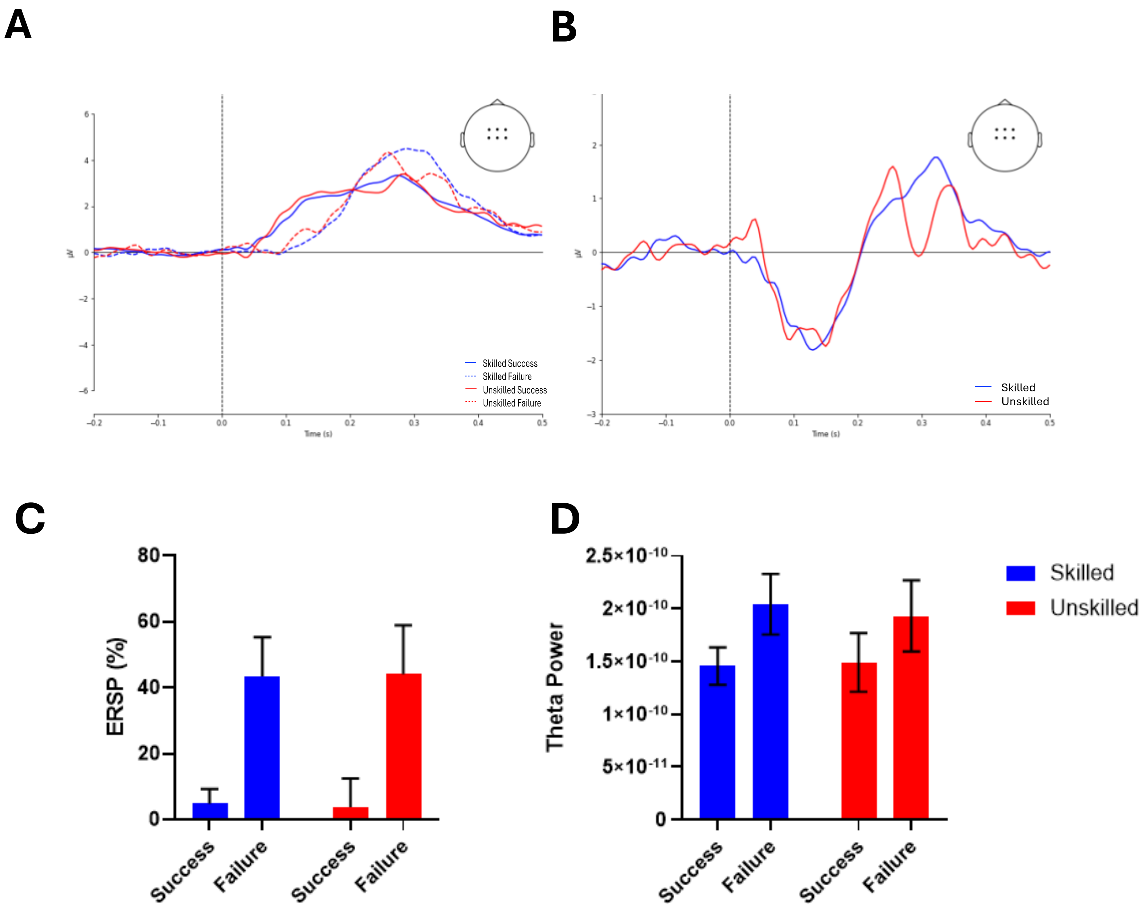


Figure 4.12. Time and frequency domain response to success and failure feedback after trial completion in frontal central electrodes (FCz, FC1, FC2, Cz, C1, C2). A) Time domain response plotting success in solid lines (blue = EP, red = NEP) and failure in dashed lines (blue = EP, red = NEP). Left is the basic ERP plotted independently; right is the difference wave computed as Failure ERP minus Success ERP across the same channels. B) Frequency domain response in the theta frequency band with the ERSP plotted comparing evoked theta data in success and failure trials (Left) and absolute theta power in success and failure trials (right).

The response to success or failure in frontal-central electrodes differs drastically based on outcome. Successful trials evoke an earlier response that is sustained for 400ms, whereas failed trials evoke a later and shorter, but higher amplitude response. There appears to be little difference between skilled and unskilled players. By plotting a difference wave, an early negative potential is revealed, referred to as error related negativity (ERN). The amplitude and latency of ERN remains stable across populations, peaking ~100ms after feedback onset. The peak positivity occurs earlier in unskilled players, with skilled players displaying a more consistent and sustained peak. Although there is no significant interaction between outcome and population for frontal theta ERSP (F(1, 83) = 0.2633, p = 0.2633), Theta ERSP is significantly different between outcomes (F (1, 80) = 77.89, p = <0.0001) but does not significantly differ between populations (F (1, 80) = 0.001085, p = 0.9738). Due to the lack of significant interaction, post-hoc analysis is not justified. There is no significant interaction between outcome and population for Theta absolute power (F(1, 83) = 0.0318, p = 0.8587). It is significantly higher in failed trials compared to successful trials (F (1, 83) = 63.25, p = <0.0001) but is not significantly different across populations (F (1, 83) = 0.04280, p =0.8366). Both theta ERSP and absolute power are significantly higher in failed trials than successful trials which is stable across populations.

Discussion

The present study seeks to identify neural correlates of high performance and isolate how they differ in a skilled population compared to an unskilled population. This population was defined based on their performance during a battery of behavioural tasks that tested fundamental movements implicit in performance on the sporting model of Esports. To identify neural correlates of fundamental movement performance, in this case flicking – a fast reflexive movement – a simple visuomotor psychophysics task was created that. Behavioural analysis of task performance revealed that skilled players show a reduced reaction time and number of errors compared to unskilled players. They also display earlier saccades but with relatively similar average saccade velocity.

Neural correlates of this higher level of performance are separated based on population/trial outcome and emerge from two different domains of brain activity. The time domain, how activity changes over time, and the frequency domain, how activity oscillates over certain frequency ranges. In the time domain, the p300 component of the occipital-parietal ERP are shown to be modulated by the skill level of the population and by the trial outcome. As expected, depending on the trial outcome, either successful or failed, modulations to the p300 amplitude were found. Specifically, a significant increase in successful trials. However, no significant differences in p300 amplitude were found between the two populations as hypothesized. Source space analysis revealed that in successful trials of skilled players, the amplitude of activation was the highest and the lowest amplitude was found in failed trials of unskilled players. This occurred globally across the brain (shown through eLORETA analysis) and in occipital-parietal labels (shown through dSPM analysis). Furthermore, skilled players displayed a larger VEP compared to unskilled players occurring between 100-200ms after stimulus onset. Finally, successful trials across both populations, displayed a reduced latency to peak VAN compared to unsuccessful trials. Multi-variate pattern analysis revealed peak decoding accuracy between skilled and unskilled players occurring over the first 300ms of the response and, across both populations, peak decoding between successful and failed trials occurs 400ms after stimulus onset and continuing to the end of the trial.

In the frequency domain, there was a difference in pre-stimulus alpha across both populations and trial outcomes, with the source localized to occipital regions. Alpha power was higher in unskilled players and both populations showed decreased alpha power in successful trials. Theta power displayed a strong and stereotyped peak occurring over the first 500ms of the post-stimulus response which was higher in unsuccessful trials. Both pre-stimulus alpha and post-stimulus theta power in successful trials showed a strong inverse relationship to performance. Low oscillatory power was associated with short reaction time. Movement-related beta perturbations occurred in two important movement periods reflecting the well established MRBD and PMBR spectral perturbations. During the movement period, unskilled players displayed greater MRBD than skilled players. However, in skilled players there was a difference between success MRBD and failure MRBD, in unskilled players this difference was negligible. With PMBR, this effect was consistent across populations, with a significant difference in PMBR in unskilled players in success trials.

P300 and its links to performance

One of the major neural correlates of performance was displayed by both populations, whereby peak p300 amplitude was larger in successful trials, found in occipital parietal electrodes (sensor-space) and labels (source-space). This finding is supported by a multitude of research focussing on p300 which regards this component as a reflection of conscious access (Rutiku et al., 2015)) . Analysis of current spectral density shows that the p300 component, induced by visual stimuli, is highly localized to occipital parietal regions (Ji et al., 1999). It is induced by visual information since it is abolished by blurring of the visual stimulus (Heinrich et al., 2010) and the source strength during p300ms in occipital parietal sensors is significantly higher during seen trials, as opposed to unseen trials (Babiloni et al., 2006). The present study replicates these findings and proposes an interesting idea for how successful responses are achieved. It is possible that failed trials occur because the visual information was not consciously accessed either at all, or in enough time for the participant to accurately respond. Each trial has a time limit (1000ms) which is incredibly short and a departure from the methodology employed by other visuomotor tasks. This choice implemented an important sporting, but especially Esports, concept of time pressure. Players in sport must react with both speed and accuracy under pressure. As expected, to respond successfully, a participant must consciously access this information quickly. Skilled players can consciously access the salient visual information more frequently, facilitating the improved performance. Evidence for an increase in speed of reaction comes from the reduced latency to VAN, a reliable indicator of visual perception (Koivisto, and Revonsuo, 2003) and is an indicator of unconscious detection (Koivisto and Revonsuo. 2010). This component displays a significant reduction in latency in successful trials compared to unsuccessful trials across both populations. Its role in unconscious visual perception suggests that in successful trials an earlier visual perception facilitates improved performance. Furthermore, unlike unskilled players, the skilled population display an increased VEP. By combining these results, it suggests that skilled players respond faster and with increased accuracy by evoking an enhanced occipital-parietal response over the early stages of visual processing.

Unfortunately, no correlation between p300 amplitude in successful trials and reaction time was found in either population. This finding does not corroborate with the vast majority of research in this area. However, many of the studies are simple visual detection tasks, asking participants to report if they had seen a stimulus or not. The present task is not so simple. Participants have 1000ms during a trial, it would be unlikely to suggest that a stimulus was not detected at all within that period. Ultimately, there is still a debate in the field about whether p300 reflects conscious awareness or unconscious perception in occipital parietal electrodes, since stimuli are perceived even when observers are unaware of the stimuli (Merikle et al., 2001). P300 theories have been updated to suggest a post-perceptual marker of conscious access not simply conscious perception (Pitts et al., 2014). therefore, there are still many steps required by the participants to execute a precise movement in time. Training interventions in older populations, have been created displaying enhanced p300 amplitude which was associated with increased cognitive performance (Yang et al., 2018). Skilled players, many of which are experienced in Esports, might display pre-trained enhancements to p300 amplitude which are captured in this study. Whilst this might facilitate an increased visual perception and overall performance, it does not linearly increase reaction time. The study didn’t report any differences in the amplitude or latency of p300 between the skilled and unskilled population in successful or unsuccessful trials, respectively. It is possible to conclude that the visual stimulus more readily enters conscious awareness of skilled players which allows for the utilization of this information to produce a conscious action more frequently. That is, it’s not the amplitude difference of p300 that causes the performance difference, but the frequency a high amplitude component is induced which produces the observed performance difference. There could also be further downstream modulations that reflect more complex cognitive/motor, processes and these are only an early indication of conscious perception or awareness. How this information is utilized further is unclear.

Neural oscillations and their link to performance

There is a wide array of research isolating the role of alpha power in visual perception research. However, the present study provides evidence for a relationship between pre-stimulus alpha power and complex movement performance. In the present study, low pre-stimulus alpha power predicted performance, showing a strong relationship to reaction time. In both populations, there was a significant correlation between low alpha power, and short reaction time.

The present study largely supports this theory across a couple of different ways. Firstly, in both populations, a reduction in alpha power is found in success trials compared to failure trials, as has been well established in the literature. However, in skilled players there is a reduction in alpha across all trials. Behaviourally, although reaction time is faster overall in skilled players, this only covers successful trials. The real performance difference is the vastly reduced number of errors in skilled players. As such, the reduction in occipital-parietal, pre-stimulus alpha, which has a significant relationship to reaction time, is present more frequently, leading to a reduction in errors. This inverse relationship between pre-stimulus alpha and performance has been repeatedly found across numerous studies (Van Dijk et al., 2008; Chaumon and Busch, 2014, Benwell et al., 2017; 2022) and has been shown to be associated with higher amplitude ERP elements post-stimulus (Iemi et al., 2017). This decrease in alpha is suggested to facilitate an increase in global excitability (Lange et al., 2013) and reflect the accumulation of evidence over time (Kloosterman et al., 2019) by reducing the threshold required to initiate a decision (Limbach and Corballis, 2016). The present study would support this idea since lower alpha power might release the visual system, direct attention towards the target and induce a motor decision output quicker, facilitating faster reaction time, but also reduced number of errors.

Predominately, research has not used such complex motor outputs however, there are several studies which would support this notion. It has been found that pre-stimulus alpha is decreased prior to the execution of successful putts in golf, relative to power in unsuccessful putts (Bablioni et al., 2008) with the strongest alpha power reductions occurring over sensorimotor areas. Golf, however, is a much less visually dominant sport than Esports since players do not adapt to rapidly changing visual stimuli. Although this result slightly differs in location to the current study, with source localisation positioning maximal alpha power decreases in the visual cortex, it proposes a link between alpha and performance of a complex movement in sport. Within more visually dominant sports, such as air-pistol shooting, a common feature of high performance is a reduced, pre-stimulus alpha power in occipital regions that precedes successful shots (Kerick et al., 2004; Del Percio et al., 2009). The authors in these cases have postulated decreases alpha power corresponds to an increase in attentional resources used by the visual system assisting performance. The present study strongly supports this idea due to the association between higher performance and low pre-stimulus alpha.

Post-stimulus theta power displayed a strong inverse relationship to performance, in a similar vein to pre-stimulus alpha power. That is, low post-stimulus theta was strongly correlated to high performance. Theta power showed a drastic increased spanning 500ms after stimulus onset in FM electrodes, however power was lower in successful trials. A potential explanation for this general increase is related to realizing the need for cognitive control (Cavanagh and Frank, 2014), coordinated by theta power in the anterior cingulate cortex (ACC) a region commonly linked to theta power (Cohen and Donner, 2013). Its statistical relationship to reaction time has repeatedly been identified (Cohen and Cavanagh, 2011; Cohen and van Gaal, 2014) however these studies often focus on conflict resolution as opposed to more explosive visuomotor performance like the present study. Regardless of trial outcome, theta power increased drastically after stimulus onset across both populations. Interestingly, theta was lower in successful trials. In unskilled players, there was very little difference in peak theta power, but a higher average theta power. Perhaps the sustained increase in unskilled players, and peak difference in skilled players explain a similar phenomenon. That is, moderations to cognitive control were important for high performance. It is possible that unsuccessful trials induced inappropriately large signalling for control that impinged performance in unskilled players.

Since EMG or motion capture wasn't utilized in the present study, it is harder to identify the exact time of movement onset, therefore elements such as movement-related cortical potentials are not possible. MRBD offers a better alternative to quantity brain activity during movement. It is seen as seen as a reliable motor potential, originating in the motor cortex (Espenhahn et al., 2017), that increases in magnitude depending on movement duration (Heinrichs-Graham and Wilson, 2015) and with reaction time (Khanna and Carmena, 2017; Darsch et al., 2020). This period has strongly been linked to motor planning which, unfortunately hasn't been captured in this study. Whilst motor planning is logically implicated in this period, it is not explicitly measured.

Unskilled players show increased MRBD magnitude, but reduced performance contravening previous findings. This questions whether these claims are true for all populations, particularly when extreme populations are used. In the present study, the populations are separated based on performance, with skilled players performing better across all tasks. These tasks, show the greatest differences in performance during Esports task, whether they are aim-training (AimLabs), aim-testing (NAM1) or full Esports (CS:GO), the difference in performance increases with complexity and ecological, Esports validity. As such, skilled players are better at making these movements, not just in this simple task, but even more so in more complex tasks. A possible explanation for increased MRBD in unskilled players comes in two forms. Firstly, it is possible that the differences are not linear, increasing in amplitude as reaction time increases, and that there is a finite point where this switches. Secondly, once a certain level of skill is reached, exemplified by very high performing players and an extreme population such as Esports players, MRBD during movement planning and/or execution is modulated by neural efficiency. Skilled Esports players have put considerable time into practicing these exact movements, just with more complex visual imagery and often linking them, rather than single action, as is tested here. Perhaps, skilled players display an increased neural efficiency to achieve a higher performing movement, one that is executed quicker (shown by reduced reaction time) and is more accurate (shown by reduced errors) because of both experience and a skill. Certain players in the skilled group, however, are not experienced and some in the unskilled group are experienced (at least with video games, but also with Esports).

Therefore, whilst MRBD has a relationship to performance, with desynchronisation a key component of fast, reflexive movements, it may be modulated by efficiency that could serve as a predictor of skill potential in non-experienced players.

PMBR and its relationship to performance is supported by the present study. In the literature, errors and error size decreases the amplitude of PMBR, something found across both populations. During successful trials there is a significant increase in PMBR compared to failure trials. Potentially, failure trials result from a decreased force applied during the movement (Houdayer et al. 2006), however since force wasn't quantified, it cannot be said with any clarity. This implies that the sensory/cognitive check, a function of PMBR, is strongest in successful trials and might serve to implement motor learning stronger because of correct movements as opposed to incorrect movements.

Furthermore, present in skilled players, was a lateralisation effect showing consistently higher beta power in the right electrodes compared to the left something that was not present in unskilled players. Although the finding of increase MRBD during successful trials aligns with previous research, the lateralisation data does not. In fact, it is in stark contrast to research on MRBD and PMBR finding strong contralateral effects (Doyle et al., 2005; Jurkiewicz et al. 2006). A potential explanation for this result comes from the movement itself. In previous studies, simple movements are made such as finger taps/button presses. In the present studies case, only right-handed movements were made to manipulate the mouse, moving it in a fast, precise manner. This movement was also made under extreme time pressure with only 1s to respond in time. In this way, more complex sensorimotor information must be access and a more dramatic transformation is required, moving a mouse in real life to move a cursor on the screen, two differing movement planes. Increasing the complexity, the speed and the accuracy required for the movement to be successful appears to abolish the lateralization effects in skilled players.

Finally, the response to feedback is a crucial element in the present study and especially within the framework of sport performance. A failed response triggered an error message informing participants of their failure and instructing them to move faster. Because of this feedback, a typical ERN response was triggered. Successful trials, not signalled with any feedback still triggered a large response, perhaps surprisingly which onset earlier than during error feedback. By calculating a failure minus success difference wave, a typical ERN ERP was formed. Since a reward wasn't used in this study, the ERN cannot be attributed to reward expectancy (Holroyd and Coles, 2002), nor is there a mismatch between actual and correct responses (Coles et al., 2001) due to feedback faithfully representing trial performance. As such, the present ERN can be attributed to competition between representations of correct/incorrect responses (Yeung et al., 2004). Although successful trials were signalled in the same way as failed trials, the absence of an error message can be seen as a form of successful feedback. This explains the large success response despite the lack of explicit feedback. Within trial performance, it appears players of all abilities respond strongly to feedback regardless of the nature of the message. The positive portion of the ERN response is hypothesized to reflect evidence accumulation rather than the negativity simply indexing task performance features (Ullsperger et al. (2010; Steinhauser and Yeung (2010).

Theta power is regarded as a key component of error related response (Cavanagh et al., 2011) showing similarities to the ERN component (Torrecillos et al., 2014). In the present study, absolute theta power and theta ERSP showed a drastic increase in failed trials compared to successful trials. On the one hand, this would be expected due to the presence of an explicit error message signalling failure, however, the ERN displayed a strong response to success regardless of the missing positive feedback. As such, one would still expect a degree of theta power modulation in theta power that is not present in successful trials. Implicated in reinforcement learning, error related theta power perturbations are seen to provide a saliency signal for motor adaptation, rather than the drive itself (Buzsaki and Draguhn, 2004; Von Stein and Sarnthein, 2000; Janker et al., 2021). In this way, errors are essential element of learning , implicit in performance development, providing an internal signal of performance evaluation.

Conclusion

The present study utilizes a complex visuomotor performance task to isolate the neural correlates of high performance, examining the differences between a skilled Esports population and an unskilled population. It has uncovered several key contributing factors towards successful trials that are induced by both populations, and some that are unique to skilled players. Across both populations, fast reaction times are correlated to a reduced number of errors. That is, fast reaction times predicts a lower error index, suggesting better performing players are both fast and accurate with their responses. An electrophysiological profile of high performance is also identified by the present study. Successful trials display a significantly reduced VAN peak latency and significantly higher peak p300 amplitude. Although there aren't any vast differences between time-domain ERPs of skilled and unskilled players, this successful ERP can be assumed to be induced more readily due to the reduction of errors. Skilled players more frequently display a reduced VAN latency more readily and increased p300 amplitude, facilitating both enhanced visual perception speed and conscious access to task-related sensory information compared to unskilled players. Furthermore, whilst differences between average pre-stimulus alpha power in successful trials are prevalent across both populations, skilled players display further significant reductions. As such, skilled players display a reduction in cortical excitability, coordinated by alpha power in occipital parietal regions, which disengages attention of task-irrelevant information. Unskilled players appear to attend greatly to the fixation cross during the fixation period, resulting in significantly longer saccade latencies in successful trials and prevents fast task switching to the target. This is supported by the early-stage differences in response whereby skilled players display a significantly increased p100 amplitude and decoding scores classifying the response differences, peak over this period in successful trials. Skilled players also display recued post-stimulus theta power, perhaps signifying an increased neural efficiency and ability to manage a high cognitive load. This is further supported by reduced MRBD in skilled players, despite a higher performance. The response of both players to feedback also highlights the strong impact error signalling has on cognition unified across all performance levels and should be considered with any training intervention.

Chapter 5

Introduction

Multi-sensory integration is a crucial process in the human brain but, harnessing information from different senses, integrating it and subsequently utilizing that information for a goal-directed purpose, is poorly understood.

In a spatial cueing paradigm, information multisensory information can be used to predict a target onset prior to a response phase. This priming of the sensorimotor system has been shown to increase reaction time (Spence and Driver, 1997). Conversely, if a target is present in the opposite side to the cueing stimulus, reaction time increases due a process called inhibition of return (IOR). In this process there is an impaired ability to return to a previously attended area (Posner and Cohen 1984) due to increased attentional resources allocated to the non-target side. In the literature, the location of targets presented on the same side as they have been cued are termed valid locations and un-cued sides are referred to as invalid locations, thus the difference in reaction time to targets in valid/invalid location is referred to as the validity effect.

In MSI models, auditory and visual information is often paired together since this is a common occurrence in nature. Common models include spatial navigation and speech. As such, the validity effect is a common method of practice, but with auditory stimuli often refers to either congruent or incongruent cues. With concurrent neuroimaging, it has been found that amplitude of early stage (200ms) negative component increased in congruent trials (where sound and word matched) compared to incongruent trials (Andres et al., 2011). During multi-sensory integration, activity from different sources might display a different time course due to visually receptive neurones exhibiting a smaller receptive field than auditory receptive neurones (Cuppini et al., 2012). Even so, auditory information that is incongruent to the presented visual information, still elicits a response with a remarkably short time course, around 100ms after auditory stimulus onset (Wildman et al., 2004). Therefore, audio-visual integration relies on both feedforward and feedback connections across different sensory processing regions to integrate and respond quickly to (Foxe, J.J. and Schroeder, C.E., 2005).

Although AVI was a key component, another important part was the ability to propagate the information encoded by the spatial cues in working memory to inform the direction of the movement delay from that period. The ability to integrate multi-modal information concurrently is not the only way MSI takes place. By manipulating the time between multi-sensory stimulation occurs, working memory is engaged so that attention to the information is maintained. In this way, research on the neural dynamics of working memory has uncovered some common mechanisms.

One of the most prominent mechanisms is how theta power coordinates working memory. Theta power is commonly detected in pre-frontal regions which has been shown to functionally connect to the hippocampus, the dominant spatial navigation and memory region of the brain (Backus et al., 2016). In the pre-stimulus phase, frontal theta power has been shown to predict successful memory encoding and predicts behavioural performance (Sweeney-Reed et al., 2016). An increase in theta power is shown before the onset of later remembered words (Scholz et al., 2017) and accurate recollections of the contextual details of memories was also associated with enhanced theta power (Addante et al., 2011). With complex visual stimuli such as pictures, increased theta power predicted their subsequent remembrance (Schneider, S.L. and Rose, M., 2016). Due to the prevalence of theta in prefrontal regions, it could be seen that it functions as an oscillatory correlate of episodic retrieval mode (Lepage et al., 2000; Buckner and Wheeler, 2001) by being activated in anticipation of a retrieval event.

Another frequency band of oscillatory power, alpha, is also implicated in memory. However, this process is theorized to correlate more with increased allocation of attentional resources, enhancing the propagation of information and mainlining working memory. Alpha synchronization has been shown to enhance the precision of item recall (Poliakov et al., 2014). This increase in alpha power is supposedly reflecting working memory maintenance and/or active inhibition of task-irrelevant information

(Michels et al., 2008). However, decreases in alpha power during a visual memory retrieval task have been found as stimulus-specific information is increased (Griffiths et al., 2019). Furthermore, higher performing, faster participants also displayed stronger alpha desynchronisation after stimulus onset. Despite these contradictions, stronger alpha power was detected as working memory load was increased and during memory maintenance, resulting in faster resynchronization (Nenerf et al., 2012). This is further supported by trial-by-trial analysis, where pre-stimulus alpha desynchronisation predicts the accuracy of memory recall Myers et al., 2014). Thus alpha oscillations during memory processes, such as retrieval and maintenance, signal internal attention and facilitate increases successful recall (Pastötter et al., 2023).

One of the most widely studied ERP components associated with feedback is error related negativity (ERN). This component is a negative deflection occurring >100ms after error feedback. Multiple theories have suggested a variety of explanations for its functions such as a mismatch between actual and correct response (Coles et al., 2001), competition between representations of correct/incorrect responses (Yeung et al., 2004), and modulations to reward expectancy (Holroyd and Coles, 2002). However, this is not the only element of feedback implicated by incorrect responses. A positive deflection occurring 200-300ms after feedback onset also appears to be a crucial element (Overbeek et al., 2005). Error positivity (Pe) as it is termed, has been shown to reflect the accumulation of evidence entering conscious awareness that an error has occurred and ERN simply indexes features of task performance (Ullsperger et al., 2010; Steinhauser and Yeung, 2010). As such, Pe is an essential element of learning , implicit in performance development, providing an internal signal of performance evaluation.

An important part of performance, whether it is within a physical, sporting framework or a more cognitive framework, is the feedback. Informing a participant whether they were successful or failed a particular trial triggers evaluation of the previous trials performance to inform future trials. Research on feedback has identified theta oscillations as a key component of error related response (Cavanagh et al., 2011) showing similarities to the ERN component (Torrecillos et al., 2014) in topographical distribution. Localized to the ACC, frontal theta increased in response to high errors peaking 200ms after feedback onset (Arrighi et al., 2016). However, theta oscillations may not necessarily drive motor adaption explicitly, since they do not predict adaption rate (Janker et al., 2021). As such theta oscillations may provide a saliency signal, engaging large scale networks related to many aspects of motor performance (Buzsaki and Draguhn, 2004; Von Stein and Sarnthein, 2000).

Methods

Participants

42 participants (26 Male, 16 Female) took part in the experiment, all of which were students at University of Birmingham. Of the participants, 23 were classified as Skilled players and 19 were classified as Unskilled players based on the methods described Methods chapter. Briefly, after reporting Esports playing time based on a self-report questionnaire, populations were determined based off Esports experience only. Players who played VG, whichever input modality, but not Esports were determined to be inexperienced. After completing various Esports and psychophysics tasks, their performance on these tasks was to perform k-means clustering and identify clusters of similarly performing player groups. Silhouette scores determined that two clusters were optimal, and players were classified based on their cluster. Their previous experience was not included as part of the classification process. All participants were right-handed, didn’t wear glasses and had no history of neurological disorders. Crucially, all participants reported some experience with video-games.

Experimental Procedure

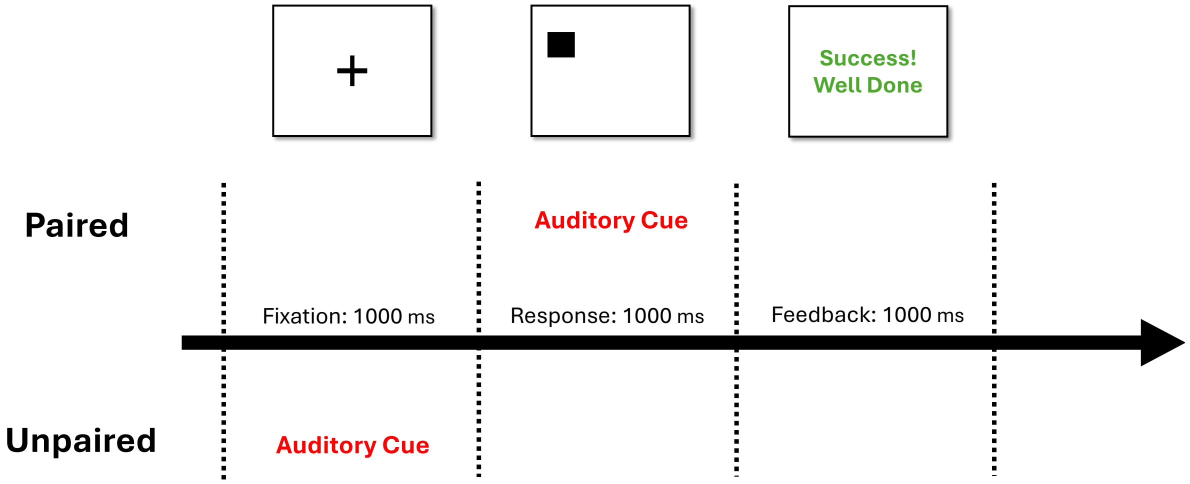


Figure 5.1 Trial design figure displaying the difference between auditory cue onset time between paired and unpaired conditions. The visual stimuli presented on the participants screen is shown above with the fixation, response and feedback stimuli being distinct.

All psychophysics experiments were created using SR Research experiment builder to accurately co-register with the eye-tracker and stimulus pc. In each experiment, a fixation cross began the trial by being present for 1000ms localizing eye fixation to the centre of the screen. After the fixation period was over, the mouse location was set to the centre of the screen and the response target, a visual stimulus, would appear on the screen. In this set of experiments, an auditory cueing stimulus was also used. In unpaired trials, the auditory stimulus was played during fixation cross period lasting for 100ms and occurred at the same time as fixation cross onset. In paired trials, the same auditory cueing stimulus occurred at the same time as target onset. The auditory stimulus faithfully predicted the location the target appeared, either to the left or right of the fixation cross. There were 50 trials to the left and 50 trials to the right per pairing condition.

The target was a small black square, projected on a white background to maximise contrast. Participants would then have 1000ms after stimulus onset to move the mouse to the target and click on it, with only clicks registering within the target boundary being registered. The reaction time, calculated from stimulus onset to a successful click, was recorded, as well as the number of failed trials, reported as errors. . If the trial was successful, a message reading “SUCCESS, WELL DONE!” would appear on the screen in bold, green lettering. If the trial was failed because a successful click wasn’t registered within the 1000ms this would be recorded as an error and a message reading “FAILURE, MOVE FASTER!” would appear on the screen in bold red lettering. After 500ms of this message being present, another trial would begin, denoted by the fixation cross reappearance. Before each block, participants would receive instructions and complete eye-tracker calibration steps. There were two blocks, one for each pairing condition, consisting of 100 trials each.

Eye-Tracking

Eye-movements were recorded using an Eyelink 1000 plus (SR Research), with eye-tracking calibration steps performed before all experimental blocks before the delivery of tasks instructions. To quantify eye-movements during the study, SR research’s data analysis tool, Data Viewer was used. This facilitated the identification of saccade, fixations, and trial reports. Due to the experimental coding being in another data package from SR research, all trials ported over contained the necessary trial condition information such as the target size, location, and calibration reports. To identify eye-movements exclusively during the trial period, a reaction time variable could be initialized which marked the moment of stimulus onset, detected by the time the host pc received the stimulus onset trigger (the same trigger received by the EEG amplifier) to the moment it received the outcome trigger, either success or failure. As such, only eye-movement event-locked to the stimulus onset were included in analysis. Saccades below 1 degree were excluded from analysis.

EEG recording and analysis

The data was acquired using a 64-channel EEG (BioSemi) and processed using MNE – python toolbox, as described in Chapter 2. The data was subjected to a number of pre-processing and processing steps as outline in the methods chapter. Briefly, noisy sensors were first removed and interpolated by RANSAC algorithm. Then the data was downsampled to 200hz to reduce computation time. After downsampling, events were marked depending on population (skilled or unskilled), event (stimulus onset or response) and outcome (success or failure). From here the data was passed through the AutoReject algorithm to reconstruct and drop extremely noisy epochs before being passed to the ICA algorithm which allowed for artefact detection and removal. Then the data was passed for a final time to AutoReject to reconstruct any remaining noisy epochs and drop any that still didn’t pass the threshold (a lower threshold than the first AutoReject pass). At this point, the now clean data was filtered from 1-30Hz (high and low-pass) and average referenced. Epochs from this position could finally be averaged together to form evoked objects, or grand average ERPs, per population, event, and outcome.

Time-domain analysis

To identify the visual stimulus related component of ERPs, occipital parietal electrodes were grouped and plotted as ERPs, event locked to stimulus onset, depending on the outcome. Stimulus onset events that were followed by events of interest were defined using the function ‘define_target_events’ allowing for new events to be created if a target event follows the original event, within a certain time-window. This allowed stimulus onset events during success trials, and stimulus onset during failure trials, to be identified separately and compared. Trials were separated based on their pairing condition.

Frequency-domain analysis

With clean and pre-processed data, Morlet waveform analysis was applied to frequencies of interest. In this experiment, the frequency ranges used were Theta (4-7Hz), Alpha (8-12Hz), Low Beta (13-21Hz) and High Beta (22-30Hz), calculating individual frequencies in steps of 1Hz. To define the number of cycles, the frequency range was divided by 2 and fast Fourier transform was applied. Power for each frequency was then averaged for time periods of interest, either pre-stimulus (-1, 0.2) or post stimulus (0, 0.8).

Statistical Analysis

Statistical analysis was conducted differently depending on the type of data, behavioural data and outputted measurements of time/frequency elements, were analysed using Prism (GraphPad). Examples of this are behavioural performance, eye-tracking, ERP measurements and power estimates. Statical analysis of complex time/frequency elements were analysed using MNE-Python. To establish a statistical relationship between time/frequency elements, outcome, and population, peak measurements of grand averages and averaged power estimates were made. These measurements were then statistically analysed using a 2-way ANOVA comparing Population x Outcome, corrected for multiple comparisons using Tukey's post-hoc test. 1-D cluster-based permutation statistics were calculated for difference waves, testing deviation from zero. An F-value threshold of 6 was used to determine a significant cluster.

Source Localization

To achieve source localization several different techniques were used to estimate both activation and power changes in the source space. To compute all solutions, a forward model was create using the standard template MRI subject fsaverage (FreeSurfer). Using Dynamics Imaging of Coherent Sources (DICSs), a volumetric forward model was created. To do this the template MRI was used to construct boundary element model (BEM) using a three-shell model (brain, inner and outer, skull).

To calculate source activations a linear minimum-norm inverse method (eLORETA) was computed and applied using a regularized noise covariance matrix. From here, the inverse solution can be calculated and source time courses obtained. To calculate event-related source power changes the DICS method was used with the volumetric forward model. Cross-spectral density was calculated for each frequency band using Morlet waveform transformations using a baseline covariance matrix (pre-trial) and an active covariance matrix (during trial), in this case, the baseline was set 1.5-1s prior to the pre-stimulus fixation cross period, where a blank screen was present after the termination of the outcome message.

Results

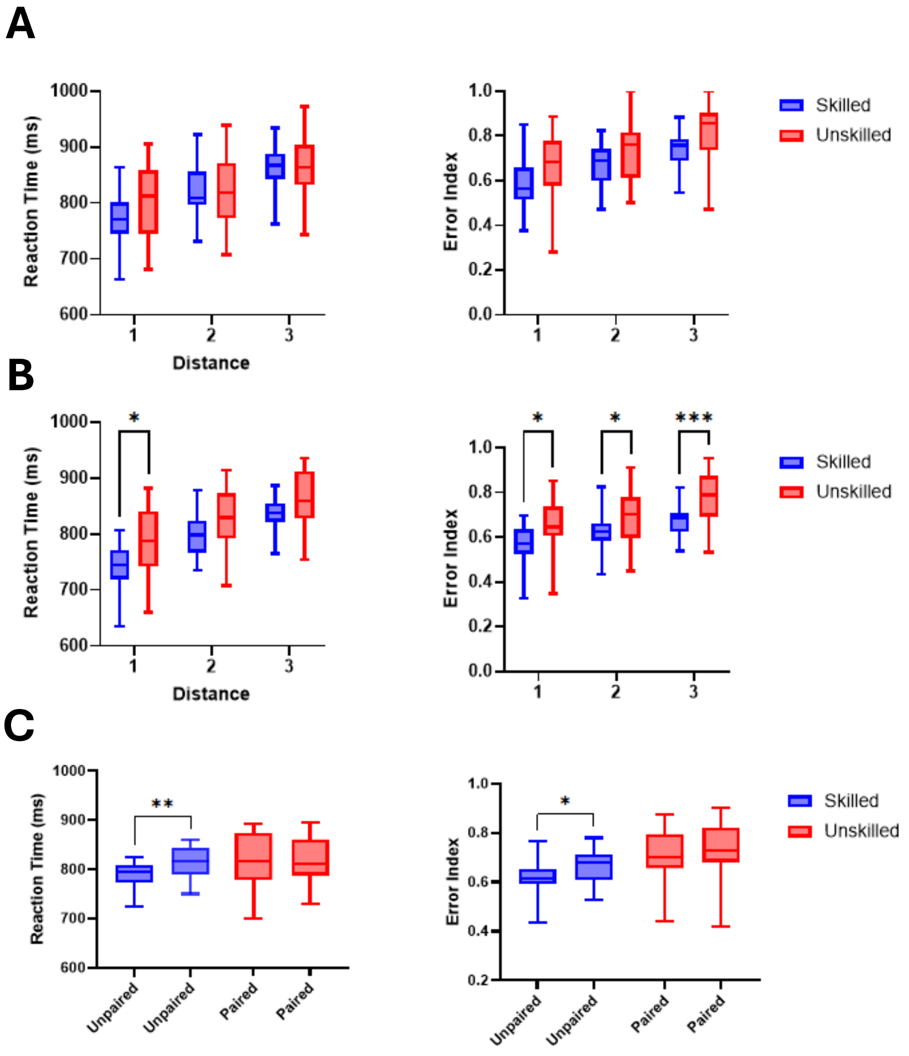


Figure 5.2 Behavioural differences in reaction time and errors across Unpaired and Paired conditions, comparing over target size. A) Reaction time across different target sizes (1, 2 and 3) and error index across different target sizes during unpaired trials. B) Reaction time across different target sizes (1, 2 and 3) and error index across different target sizes during paired trials. C) Average reaction time and error index across all target sizes comparing skilled and unskilled players in unpaired and paired trials. A and B analysed using 2-way ANOVA comparing target size and population. C uses unpaired t-test to compare the difference between population only per condition.

The behavioural results indicate significant differences between skilled and unskilled players deal with multi-sensory information. In paired conditions, there is a significant difference in performance across the different target sizes (F (1.865, 72.73) = 39.79, p = <0.0001) but not across the two populations (F (1, 39) = 1.005, p = 0.3223). Tukey's multiple comparison post-hoc test indicated no significant differences across any target size between populations (1, p = 0.0762; 2, p = 0.9834; 3, p = 0.6759). There is also a significant difference in number of errors across target size in paired trials (F (1.988, 77.52) = 30.74, p = <0.0001) but not across population, although it is significantly trending (F (1, 39) = 3.889, p = 0.0557). Tukey's multiple comparison post-hoc test indicated no significant difference in number of errors across any individual target size between populations (1, p = 0.1302; 2, p = 0.1725; 3, p = 0.0723). In unpaired trials, there are significant differences in reaction time across target sizes (F (1.675, 65.31) = 94.79, p <0.0001) and population (F (1, 39) = 5.848, p =0.0204). Tukey's multiple comparison post-hoc test indicated a significant difference in reaction time at target size 1 (p = 0.0115), a significant trend at target size 2 (p = 0.0517) and an insignificant difference at target size 3 (p = 0.1686) between skilled and unskilled players. The number of errors showed significant differences across target size (F (1.821, 71.01) = 45.95, p<0.0001) and across populations (F (1, 39) = 9.677, p =0.0035). Tukey's multiple comparison post-hoc test indicated a significant reduction in errors in skilled players across all target sizes (1, p = 0.0285; 2, 0.0402; 3, p = 0.001). Overall, there is a strong general trend towards skilled players performing better across both pairing conditions than unskilled players. This is displayed by shorter reaction time across all distances and fewer average errors. In the cued, unpaired MSI integration paradigm, a greater difference emerges. Finally, comparing the change in performance between unpaired and paired conditions within each population, skilled players show a significant decrease in reaction time in unpaired conditions (p = 0012) and a significant reduction in errors (p = 0.0161). Unskilled players show no significant difference in reaction time (p = 0.08847) or errors (0.7385). The performance of skilled players is significantly higher in unpaired conditions than in paired conditions, whereas unskilled players performance its statistically indistinguishable.

Time-Domain Analysis

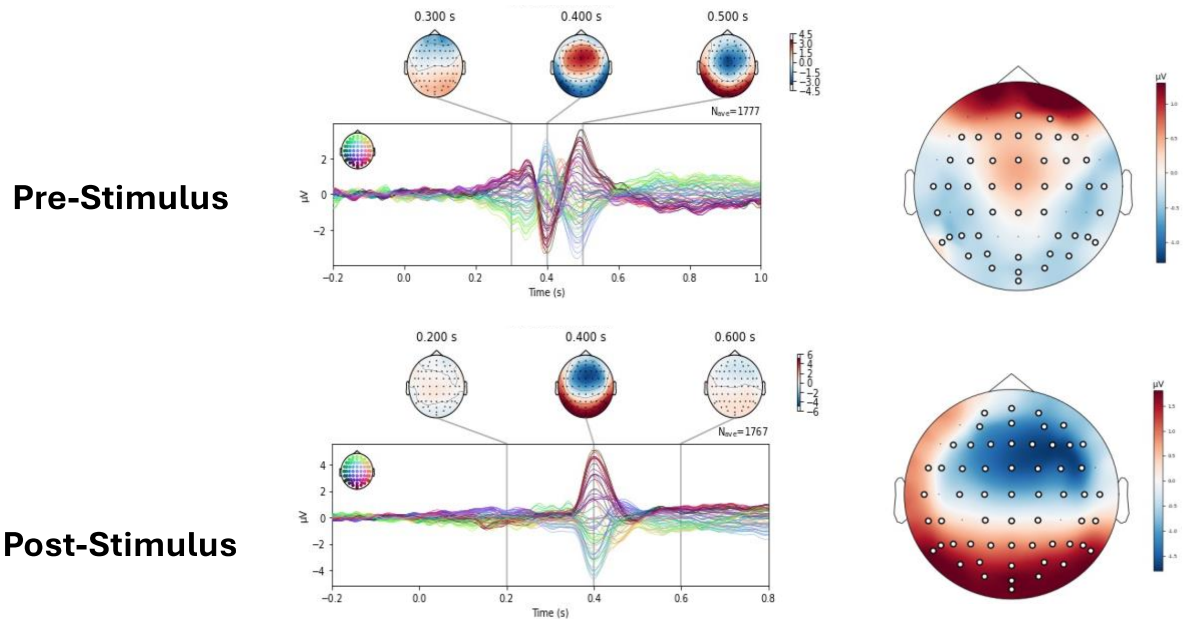


Figure 5.3. Time-domain response in the pre-stimulus onset period and post-stimulus onset period computed as unpaired minus paired waveforms in butterfly plots (left) and scalp maps (right). High positive voltage is displayed as red and low negative voltage is displayed as blue. Sensors significantly deviating from 0 are highlighted.

The butterfly plots display a large difference in responses to the AV pairing conditions across all participants occurring differently across electrodes sites. In both conditions, a large dipole emerges 200ms after visual stimulus onset, with a large positive anterior potential and large negative posterior potential . In both trials, a second dipole occurs 300-400ms after stimulus onset, except it is significantly larger in paired AV trials. The difference wave displays the magnitude of this difference, peaking at 400ms and topographical distribution of significantly different electrodes is plotted.

The voltage change over time during paired and unpaired auditory visual stimulus trials display vast differences between them. Starting with frontal electrodes a sharp negative potential is observed in paired trials peaking at 400ms after stimulus onset. This potential is not present in unpaired trials. In central electrodes a similar, less sharp potential occurs in central electrodes occurring at a similar time, again this is not in unpaired trials. Finally, in occipital parietal electrodes a strong negative potential occurs at 200ms after stimulus onset in paired trials, and then a strong positive potential occurs at 400ms after stimulus onset in paired trials. It appears there are two dipoles across the entire brain present in the data, one occurring at 200ms after stimulus onset, which is stronger in unpaired trials and one occurring at 400ms after stimulus onset which is occurring 400ms after stimulus onset. These dipoles reverse in orientation between the first and second one.

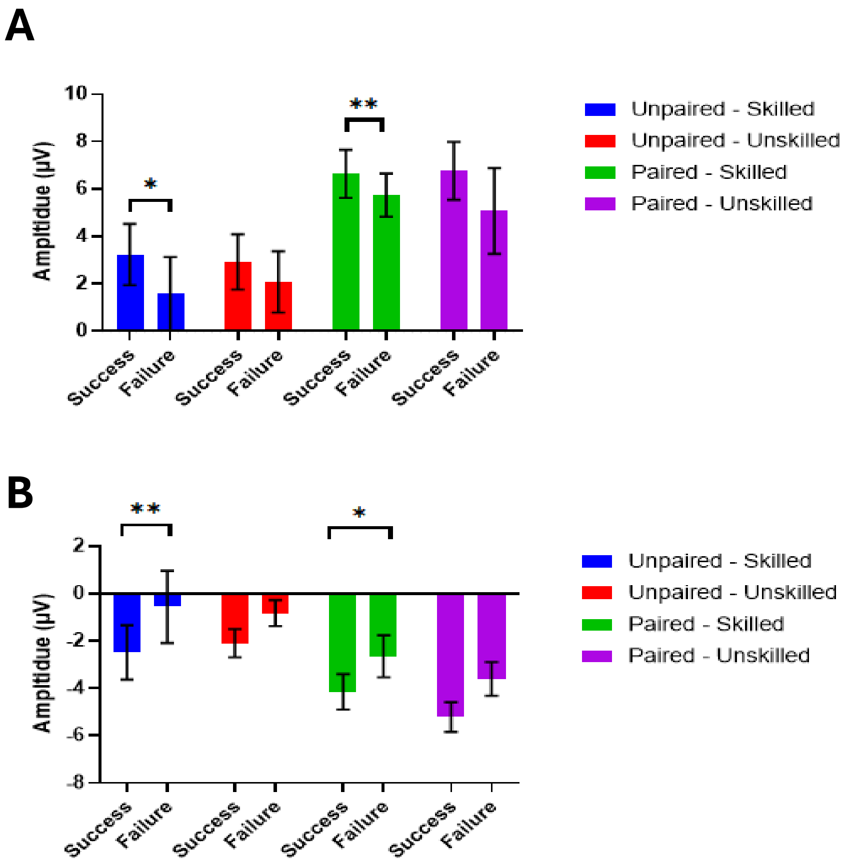


Figure 5.4. peak amplitude of unpaired and paired trials across success and failure trials, in key brain regions. A) Peak amplitude measurements of occipital-parietal electrodes. B) Peak amplitude measurements of frontal electrodes. Trial measurements occur between 350-450ms.

The peak amplitude measurements show several differences both between location, pairing condition and outcome. The interaction between outcome and condition/population is significant (F(3,78) = 4.179, p = 0.0186) for occipital parietal electrodes and for frontal electrodes (F(3,78) = 5.026, p = 0.0081). In occipital parietal electrodes, there is a significant difference in amplitude between outcomes (F (1.000, 44.00) = 22.85, p = <0.0001) and between pairing conditions (F (1.000, 44.00) = 38.82, p

= <0.0001), however there is no significant differences across population (F (1, 44) = 0.02290, p = 0.8804). Tukey's multiple comparison post-hoc test indicated a significant difference between successful trials in unpaired conditions of skilled players (p = 0.0477) and in paired conditions (p = 0.0073). There were no significant differences in unskilled players (unpaired, p = 0.22; paired, p = 0.1809). In frontal electrodes, there are significant differences between successful and failed trials (F (1, 44) = 25.96, p = <0.0001) and between pairing conditions (F (1, 44) = 12.53, p = 0.001) but there are no significant differences across populations (F (1, 44) = 0.4889, p = 0.4881). Tukey's multiple comparison post-hoc test indicated there are significant differences between successful and failed trials in unpaired conditions of skilled players (p = 0.0089) and in paired conditions (p = 0.049). However, there are no significant differences between conditions in unskilled players (unpaired, p = 0.1203; paired, 0.2053). Across the different pairing conditions, there is a significant increase in voltage, either positively or negatively across all electrode sites, between the unpaired and paired conditions. In paired conditions, there is a drastic change of voltage. Finally, there are general trends in the difference between success and failure trials that remain stable between the two populations. In several cases, the amplitude is larger in successful trials than in unsuccessful trials across both skilled and unskilled players. As such there are a number of differences in peak ERP amplitude between electrode sites, between pairing conditions, between outcomes and between skilled and unskilled players This displays how multi-sensory processing differs depending on how the stimuli are paired, the outcome and the skill level of the participant.

Frequency-Domain Analysis

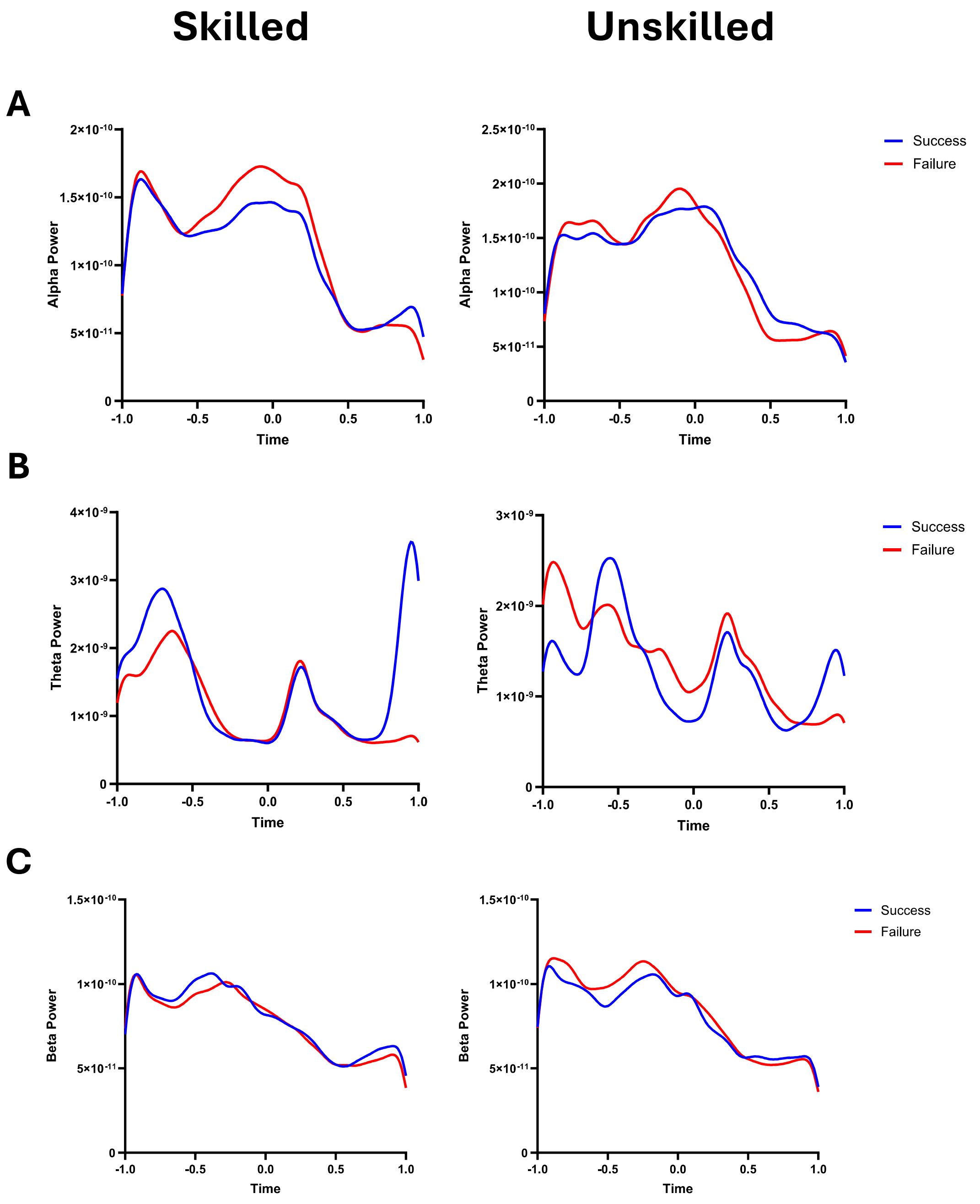


Figure 5.5. Power time course during pre/post stimulus during paired trials across skilled and unskilled players. A) alpha power time course. B) theta power time course C) beta time course.

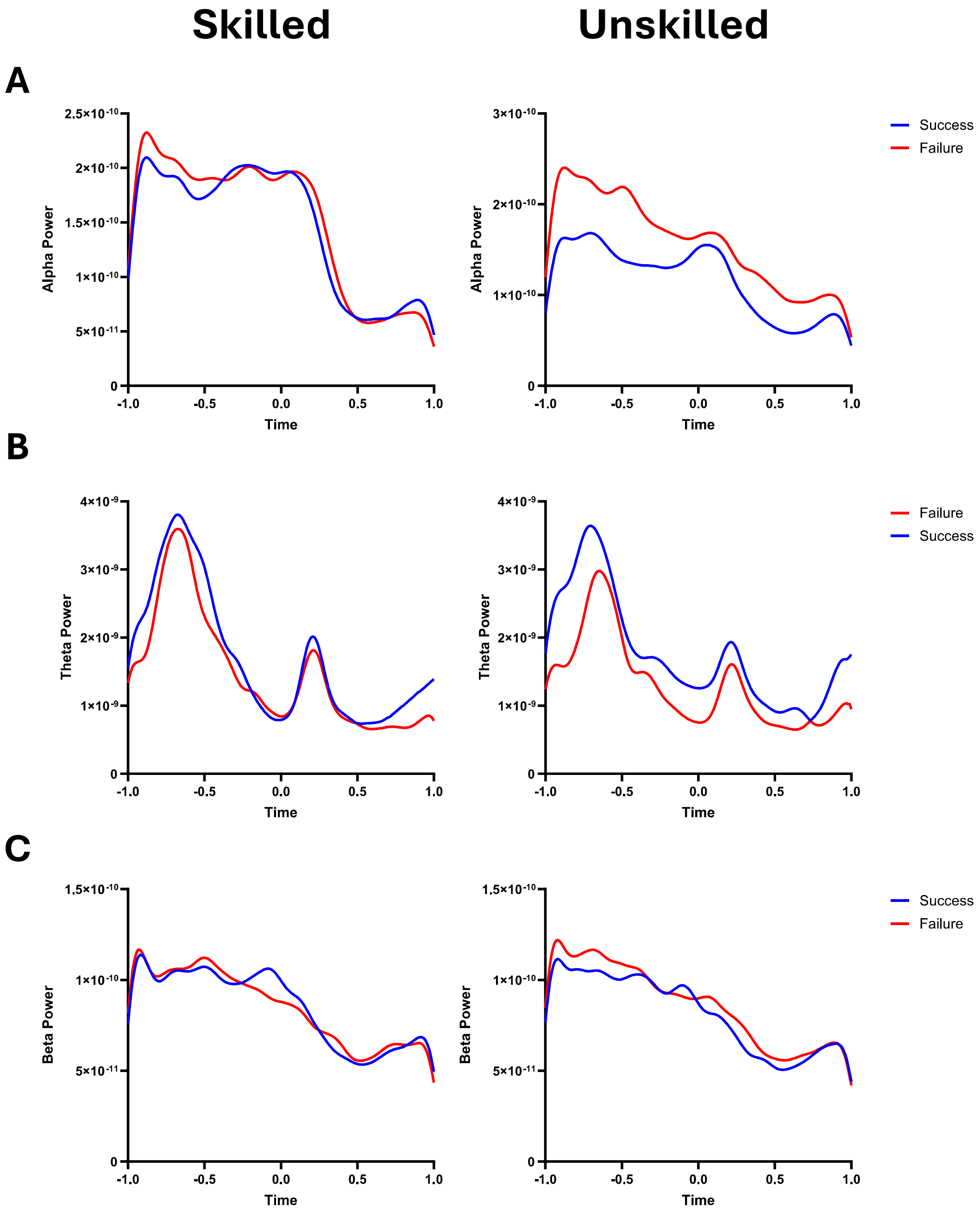


Figure 5.6. Power time course during pre/post stimulus during unpaired trials across skilled and unskilled players. A) alpha power time course. B) theta power time course C) beta time course.

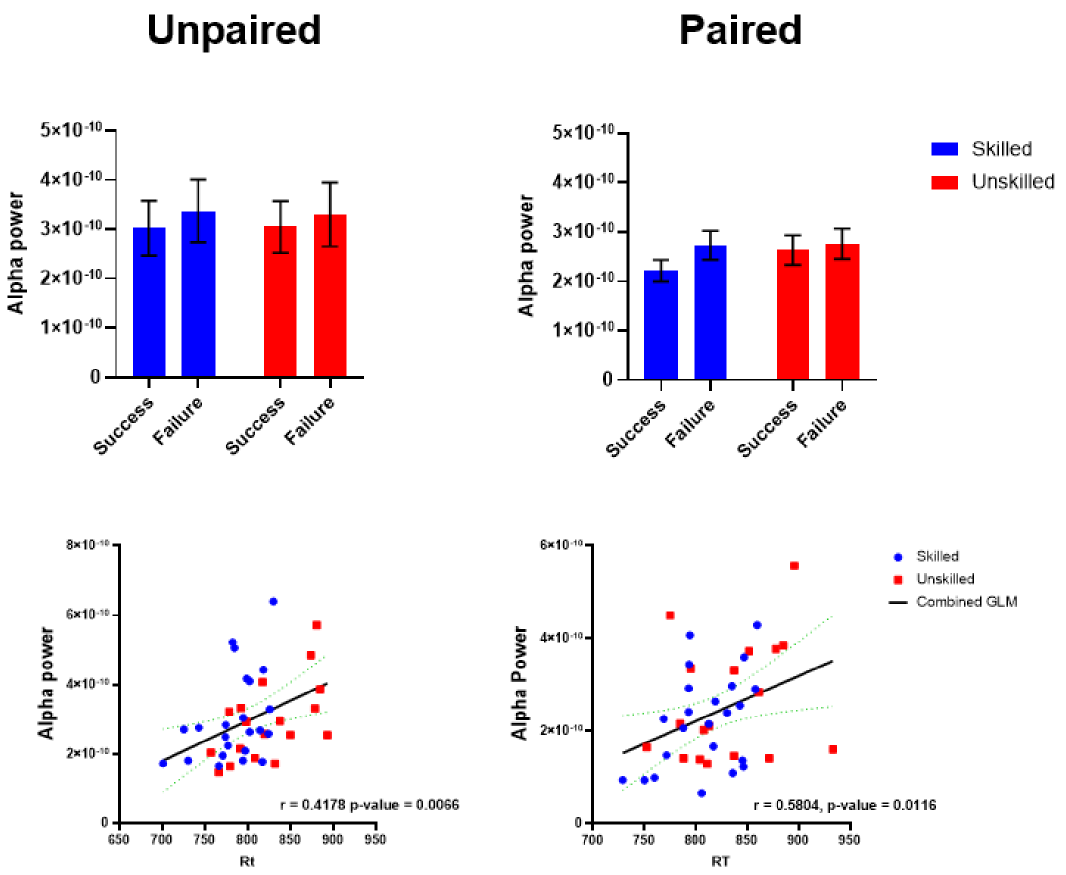


Figure 5.7. Alpha oscillatory difference between skilled and unskilled players, in success and failure trials across paired and unpaired conditions. Displaying bar charts of the difference and correlation between alpha power and performance as reaction time.

The two pairing conditions produce differences in alpha power localized to the posterior portion of the brain, the occipital parietal region. In the pre-stimulus period of unpaired trials. The interaction between population and outcome is not significant in alpha power for paired (F(1, 39) = 2.274, p = 0.1396) or unpaired (F(1, 39) = 0.6902, p = 0.6902) alpha power. However, there is a significant difference in alpha power across trial outcomes (F (1, 39) = 6.200, p = 0.0171) but not between populations (F (1, 39) = 0.3552, p = 0.5546). The lack of significant interaction means post-hoc analysis isn’t justified. In unpaired trials, there was a significant difference in alpha power depending on trial outcome (F (1, 39) = 6.160, p =0.0175). but not between populations (F (1, 39) = 0.003691, p =0.9519). The lack of significant interaction means post-hoc analysis isn’t justified. During the pre-stimulus period in unpaired trials, the auditory cueing signal has been received whereas in paired trials, the cueing signal has not. The presence of the signal increased posterior alpha power. Successful trials were associated with lower alpha power across both conditions. Correlational analysis shows a significant relationship between pre stimulus alpha power and performance in both paired and unpaired trials. In both populations there is a strong inverse relationship between alpha power and performance, shown by a positive relationship between alpha power and reaction time (unpaired, r = .0.4178, p = 0.0066; paired, r = 0.5804, p = 0.0118) therefore, lower alpha power is correlated with lower reaction time, which would yield a higher performance. As such, low-pre stimulus alpha is a predictor of performance in occipital parietal regions, regardless of the presence of a auditory predicting cue. However, by using Fisher's r-to-z approach, comparing correlations, there is no significant difference between populations (z = -0.963, p = 0.168).

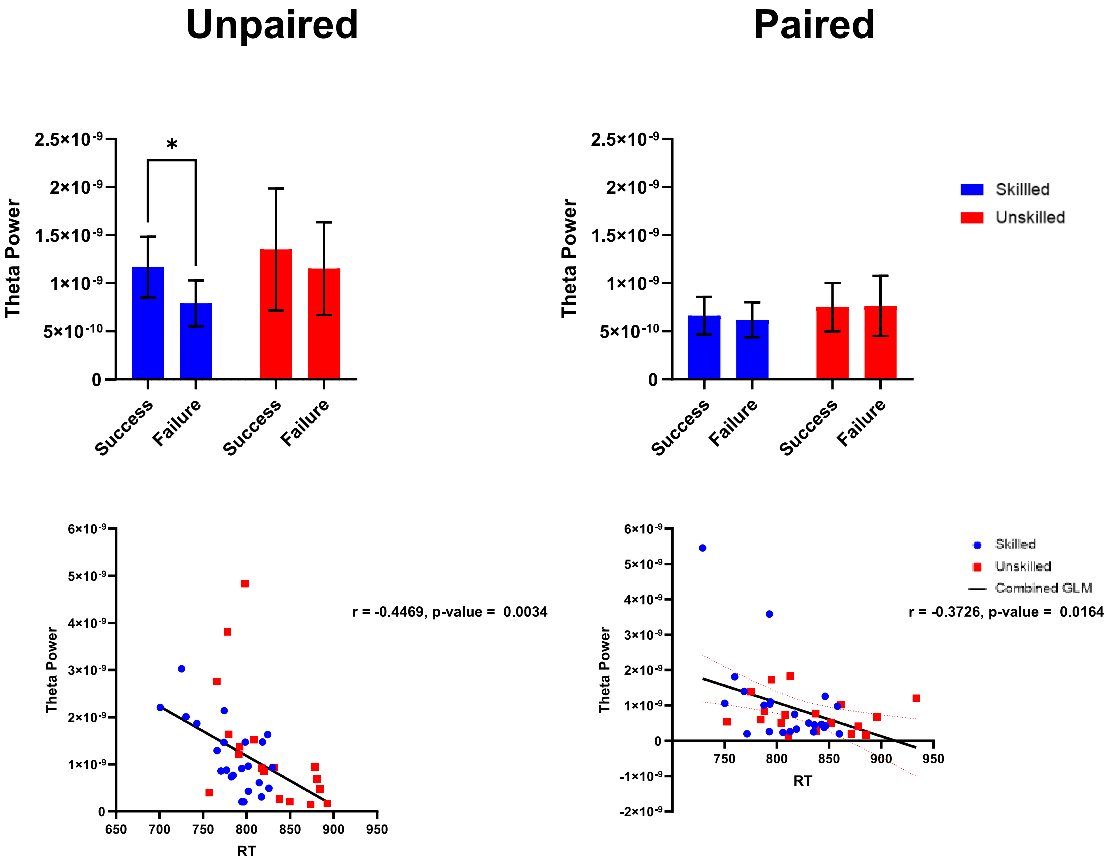


Figure 5.8. Theta oscillatory difference between skilled and unskilled players, in success and failure trials across paired and unpaired conditions. Displaying bar charts of the difference and correlation between theta power and performance as reaction time.

Theta power in frontal regions shows a significant difference between population, trial outcome and pairing condition. The interaction between outcome and population is insignificant for both unpaired (F(1,39) = 0.5451, p = 0.4647) and paired (F(1, 39) = 0.2118, p = 0.6425) for theta power. In unpaired trials there is a significant increase in theta power in successful trials compared to failed trials (F (1, 39) = 5.739, p = 0.0215) but between populations (F (1, 39) = 1.150, p = 0.2901). In paired trials, there were no significant differences in theta power across different trial outcomes (F (1, 39) = 0.06105, p = 0.8061) or across populations (F (1, 39) = 0.6438, p =0.4272). The lack of significant interaction means post-hoc analysis isn't justified. In both pairing conditions, there is a significant negative relationship between post-stimulus theta power and reaction time (unpaired, r = -0.4469, p = 0.0034; paired, r = -0.3726, p = 0.0164). That is, higher theta power is correlated to low reaction time, or high performance. However, by using Fisher's r-to-z approach, comparing correlations, there is no significant difference between populations (z = = -0.395, p = 0.347). Post-stimulus theta power shows significant increases in successful trials and higher power in unpaired cueing conditions.

Outcome Response

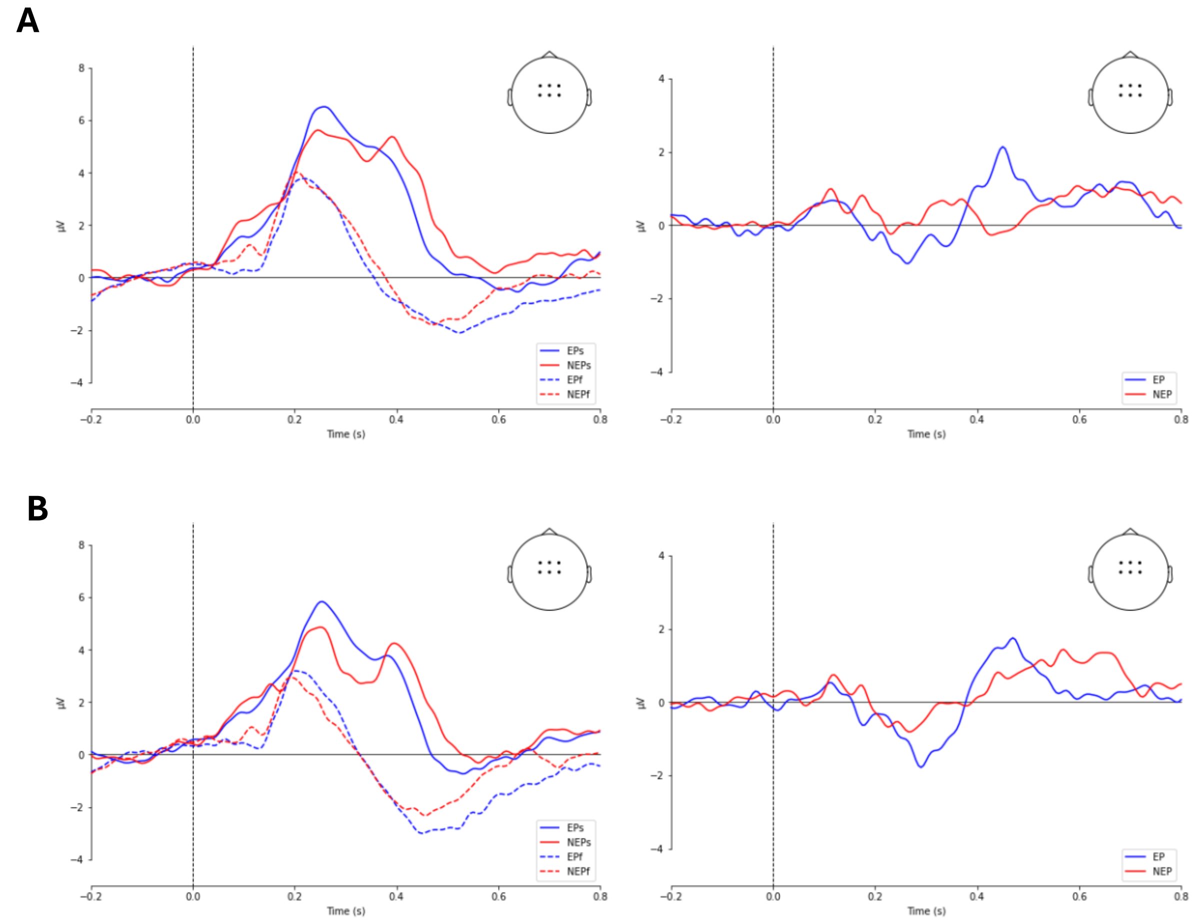


Figure 5.9. Timed domain response from Central electrodes displaying error related negativity and error related positivity in skilled and unskilled players.

Event related potential changes to success and failed trials do not vary strongly between skilled and unskilled players. Successful trials, produce a far greater response than failed trials, shown by a significantly larger peak amplitude. There appears to be relatively little differences between the two pairing conditions, with similar peak amplitudes across successful and failed trials regardless of pairing. The differences waves do not produce the stereotyped event related negativity, commonly associated with this type of feedback.

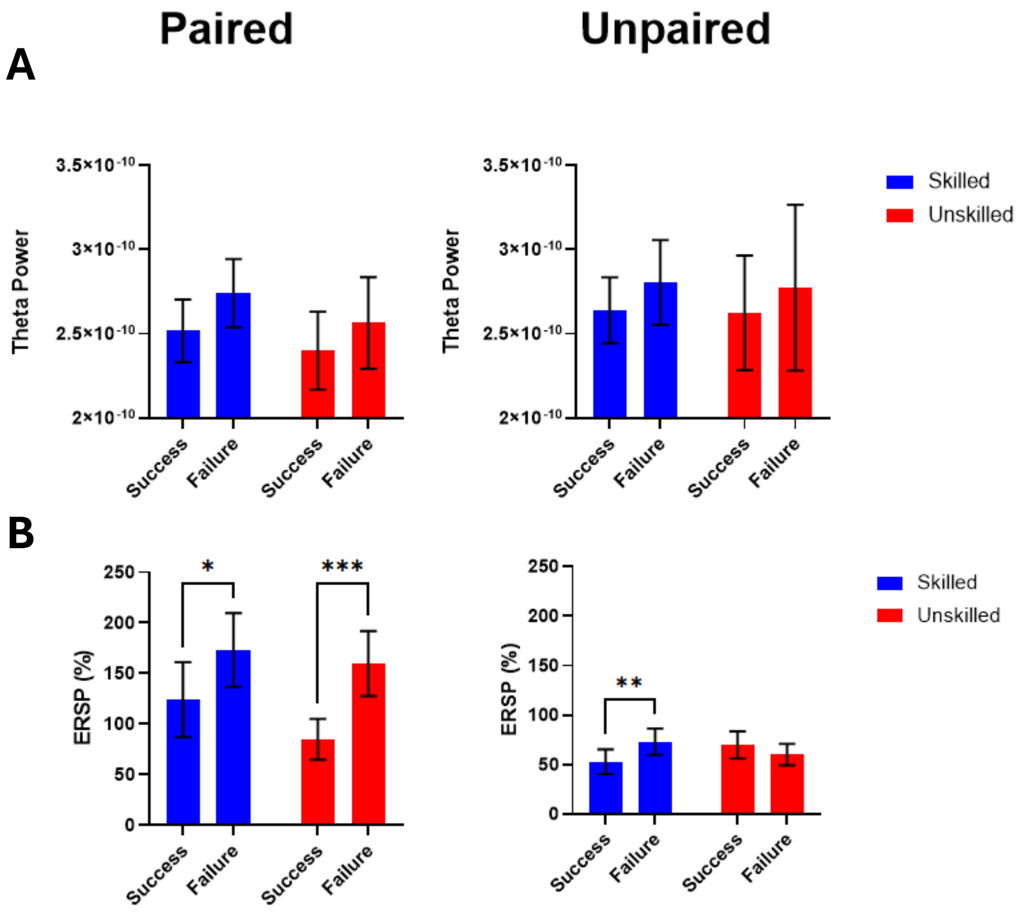


Figure 5.10. Theta power modulations post-trial during trial outcome feedback in paired and unpaired conditions. A) Theta power differences across successful and failed trials in paired and unpaired. B) Event related spectral perturbation in the theta frequency band.

Across both pairing conditions, failures produce a greater theta power response compared to successes. However, there is no significant interaction between outcome and population in post response theta power in paired (F(1,39) = 0.1605, p = 0.6908) or unpaired (F(1,39) = 0.0049, p = 0.944) conditions. In unpaired conditions, there is a significant increase in frontal-central theta post feedback in failed conditions (F (1, 39) = 7.299, p = 0.0102) but no significant differences between populations (F (1, 39) = 0.2328, =0.6322). The lack of significant interaction means post-hoc analysis isn't justified. Theta ERSP shows similar post-feedback dynamics to absolute theta power. There are significant interactions between outcome and populations in post reponse theta ERSP in paired (F(1,39) = 3.2791, p = 0.0392) and unpaired (F(1,39) = 8.451, p = 0.0060) conditions. In paired conditions, theta ERSP shows a significant difference between trial outcomes (F (1, 39) = 19.99, p = <0.0001) but not between populations (F (1, 39) = 0.3290, p = 0.5695). Tukey's multiple comparison post-hoc test indicated that for each population, there was a significant increase in post-feedback theta power (skilled players, p = 0.0109; unskilled players, p = 0.0009). In unpaired conditions, theta ERSP showed no significant differences across trial outcomes (F (1, 39) = 1.024, p = 0.3178) or populations (F (1, 39) = 0.01168, p = 0.9145). Tukey's multiple comparison post-hoc test indicated that for skilled players, there was a significant increase in theta ERSP in failed trials (p = 0.0052) but not in unskilled players (p = 0.2133). Post feedback theta power changes depending on trial outcome, with a significant increase in failed trials. Theta ERSP shows a similar trend in paired trials, but depends on the population in unpaired trials.

Discussion

The present study seeks to address how multi-sensory information is processed in the brain during complex movement tasks. By using a spatial cueing paradigm, auditory information predicts the direction of visual target onset which requires a fast and precise motor response. The two conditions of the experiment modulate the time before the auditory cueing stimulus onset with the first occurring 1000ms before target onset and the second occurring simultaneously with the visual target. In this way, audio-visual information is either unpaired (1000ms before target onset) or paired (simultaneously with target onset). Behaviourally, skilled players displayed faster reaction times and fewer errors across both conditions, with a high level of significance in unpaired conditions. The audio-visual integration (AVI) occurring at target onset increased the difficulty of the task, harming performance in both populations. However, in skilled players, the significant improvement in performance, occurring in the unpaired condition, displays how skilled players poses a greater ability to utilize multi-sensory information which in turn improves performance. This is a common concept in sport whereby utilizing salient information to inform cognitive responses is generally associated with a higher skill level.

The paired condition produced a significantly different response to the unpaired condition, inducing a drastic dipole occurring from anterior to posterior regions, 400ms after auditory cue onset. This response appears to directly relate to the processing of the auditory stimulus since it is present in the pre-stimulus period of unpaired conditions, when the cue occurs before visual target onset, and in the post-stimulus period of paired conditions, when both auditory and visual information is presented simultaneously. Furthermore, this potential is not present in the psychophysics tasks in the previous chapter using the same targets and same complex movement. The peak amplitudes of the response in anterior electrodes, covering frontal central regions, and occipital parietal regions, in paired trials displays a higher amplitude to the response at the same timepoint in unpaired trials. Across all conditions, there is relatively little difference in ERP component amplitude between skilled and unskilled players, but both populations display significant differences between successful and failed trials. Successful trials are associated with a higher amplitude occurring in between 350-450ms. As with the previous chapter, and the associated research on increased p300 amplitude and visual perception performance, higher amplitude late-stage ERP components appear to be a crucial indicator of sensory perception/conscious access to sensory information.

In the present study, there were stark differences in oscillatory power between the paired and unpaired conditions, in the pre-stimulus period. During this period, there was higher average alpha and theta power, localized posteriorly and anteriorly, respectively, across both populations. In paired conditions, where participants had not received the auditory cue, there was a generalized reduction in occipital parietal alpha power in success trials compared to failure trials. This difference was significant in skilled players but not in unskilled players. The paired trials also showed a greater recruitment of the parietal cortex compared to unpaired trials, where there was a stronger bias to the occipital lobe. In unpaired trials, the reduction in alpha power was still prevalent in success trials compared to failure trials. However, no significant differences were found. Theta power, localized frontally in both paired and unpaired trials, showed a significant increase in unpaired trials, and higher power in success trials, a marked difference to posterior alpha power. The difference was significant in skilled players and but not in unskilled players, although it was statistically trending. Both alpha and theta oscillatory power predicted performance in the subsequent trials, however they each had a different relationship to performance. Low pre-stimulus alpha strongly predicted low reaction time or high performance. Whereas high pre-stimulus theta, especially in unpaired trials, strongly predicted low reaction time or high performance.

Source localization positioned pre-stimulus alpha and theta in different positions. For alpha power, the pre-stimulus activity was localized to the occipital-parietal region. In the unpaired AV tasks, where the pre-stimulus period was combined with an auditory cue predicting target location onset, the activity was more widespread into the parietal cortex over more sensory-motor areas, compared with the paired, non-pre stimulus cued condition. Multiple studies have localized multi-sensory integration to take place in a wide variety of cortical and sub-cortical structures. The area activated is subject to a wide variety of factors including, the experimental approach, complexity of information and attention (Gao et al., 2023).

Finally, after the trial is completed, a feedback signal is presented to the participant displaying either a reward message for successful trials, or a punishment message for failed trials. The two outcome feedback messages induced differing reactions, with a greater response to punishment than reward across both trial conditions. By plotting an error-related negativity (ERN) difference wave, where successful outcomes are subtracted from failed outcomes, a strong negative ERP is shown peaking around 300ms after feedback onset. The ERN was stronger in paired trials compared to unpaired trials. Theta power localized to central regions, increases significantly after failed trials compared to successful trials. Although the total power was higher in unpaired conditions, the event-related spectral perturbation occurring in paired trials was drastically higher.

The paradigm used in the present study modulates two distinct but linked processes. Firstly, inhibition of return (IOR), whereby participants can reduce their visual search field based on cueing information and second, multi-sensory integration (MSI), whereby a participant processes two distinct sources of sensory information simultaneously. Importantly, two further modulations are considered. Firstly, are the neural correlates of IOR and MSI different during success and failure trials. Secondly, are neural correlates different depending on a skilled and unskilled population. Spatial cueing paradigms have shown that responses to cued targets presented in valid locations (same side as cue) are faster than responses to targets at invalid locations. Cues presented in this manner provide meaningful and salient information about the target onset, focussing attention to narrower areas. The present study used this concept to see if higher-skilled players could utilize a short sound to inform response, improving performance either if it was provided a substantial time ago, or if it was provided simultaneous. By creating the experiment in this way, participants had to propagate the cued information in their working memory or perform multisensory integration. In this way, only relevant information is extracted from the environment and the efficiency of information search increases due to the exclusion of extraneous information (Klein, 1988; Klein & MacInnes, 1999). However, it has been suggested that there is a temporal window whereby this is true.

As such, when analysing the results, it is important to understand how the experimental paradigm impacts the brain areas that are activated most strongly. In the present studies case, several choices were made with that in mind. Firstly, the time between cueing stimulus and response. The cueing stimulus either occurred 1000ms before or simultaneously, providing different lengths of time whereby information from the cueing stimulus would need to be retained . Secondly, the cueing stimulus faithfully predicted target onset direction. In other words, if a sound was heard in the left ear, the stimulus would always appear to the left. Although the participants were not informed of this, association would be likely to form. These two choices were made deliberately for ecological validity of the sporting model of Esports. In Esports, an artificial/virtual world, perceptual sensory information is not naturally available as it would be in traditional sports in the real world. For example, even without the present of visual cues, a player can detect the presence of an opposing player moving towards them due to the sound of footsteps or breath. This stimulus is therefore looming and will give temporal clues about the time they have to respond. Sport psychology would postulate that better players are more attentive to these cues or at least, are able to utilize this information better than worse players. In Esports, this sound is artificially pumped into the game to create a more natural perceptual environment. Actions in-game create sound to give spatial cues about where players are both in terms of distance and direction. The most important of these cues in FPS Esports is footsteps. However, many FPS Esports have ways in which a player can reduce or muffle their footsteps at an expense of manoeuvrability, namely crouching. Therefore, the sounds are often short, non-looming and difficult to discriminate. In the present study, an increase in performance in skilled players was found in cues occurring 1000ms prior to target onset, outside of the stimulus onset asynchrony window. In unskilled players, there was a slight decrease in performance with unpaired trials, although this wasn't significant.

One potential explanation for this finding is that the concept of inhibition of return is being tested in an extreme population. Skilled Esports players, and VGPs in general, routinely employ visual search, followed by a precise motor response. Research has found better visual search strategies and performance, as well as increased visual processing speeds in VGPs compared to novices. In the present population, defined (in part) by performance in FPS Esports where visual search is of paramount importance to success, skilled players appear to utilize the cued information, improving reaction time and reducing errors. As expected, the performance of skilled players was higher than that of unskilled players, especially during unpaired trials. This shows how they can retain and utilize multi-sensory information to execute a better movement. Therefore, cueing information improves performance by inducing IOR, narrowing visual search to a smaller area. Better players can utilize this more effectively.

ERPs and p/n400

The p/n400 occurring in anterior and posterior regions is significantly bigger in amplitude in paired conditions that in unpaired conditions. The same potential can be found during the pre-stimulus period in unpaired condition, 400ms after auditory onset. It appears this occurs due to the temporal synchrony of the auditory stimulus, reverberating through the brain 400ms after receiving it. Dipole localization places a strong dipole in sensorimotor regions of the brains across both populations, a region commonly associated with MSI. Although there are few differences between skilled and unskilled players, it appears that this potential has a strong relationship to performance due to its significant correlation with performance and reduced amplitude in unsuccessful trials.

The p/n400 component has been identified in previously studies and appears to reflect a mismatch in audiovisual information (Yin et al., 2008). It is possible that the potential reflects feedback connections from multisensory areas or projections from the auditory cortex to the visual cortex, explaining its relatively late onset (Calvert et al., 1999). This is supported by anatomical evidence from monkeys displaying the described connections (Falchier et al., 2002; Rockland and Ojima, 2003). As such, the mismatch in frontal negativity and posterior positivity, has been seen to reflect cogntitve integration of multisensory information across the brain (Liu et al., 2009). The present study accurately recreates this concept by displaying the p/n400 mismatch in unpaired minus paired post-stimulus onset period.

ERP amplitude of occipital parietal p300 in unpaired conditions, recreates the previously identified visual perception amplitude differences between successful and failed trials. That is, that the peak amplitude of p300 in successful trials is significantly higher than in failed trials. This is a key amplitude for conscious access and seems not to be modulated by any cueing information. It was hypothesized that there would be an increase in visual perception speed brought on by cueing information, but this is not the case. Later stage ERP components in unpaired conditions still reflect conscious access to visual information with similar temporal dynamics regardless of the presence of additional predicting information.

Neural Oscillations in MSI and WM

The stark increase in alpha and theta power in unpaired conditions potentially reflects the auditory cue functioning as a working memory. In this way, performance is improved because participants retain a memory of target direction and utilize it to narrow the attentional search area. Many studies have linked alpha and theta power to memory in a variety of ways. Theta, localized to the pre-frontal cortex has been implicated in the functional relationship between hippocampal and frontal areas facilitating communication between these two areas (Backus et al., 2016). Increases in frontal theta power has been shown to successfully predict behavioural performance in memory encoding and retrieval tasks (Sweeney-Reed et al., 2016) , showing increases in word-remembering (Scholz et al., 2017), contextual details recall (Addante et al., 2011), and complex visual stimuli (Schneider and Rose, 2016). As such, theta power increases are seen as a function of episodic memory retrieval (Lepage et al., 2000; Buckner and Wheeler, 2001). During unpaired trials, the pre-stimulus theta power functions to encode the auditory stimulus as a memory, displayed by an increase in theta power, which is retrieved post stimulus onset to improve performance. Alpha power's role in memory is intrinsically related to attention, whereby increases reflects attentional resource allocation. Increases in alpha through ERS have been associated with memory recall (Poliakov et al., 2014), memory retention (Bastiaansen et al., 2002) and memory load (Nenerf et al., 2012). It appears that inhibits task-irrelevant information (Michels et al., 2008) and signals internal attention (Pastötter et al., 2023) facilitating successful recall and improving memory performance. ERS was not found in the present study, in fact, the opposite (ERD) was observed in the alpha frequency band.

However, a key issue with the present study is the lack of modulation to memory load. Many studies have manipulated this variable to observe differences in oscillatory power directly induced by memory processes. This was not manipulated here and as such it is difficult to truly attribute changes pre-stimulus onset directly to memory. Although it is likely that the auditory stimulus was, in some way, encoded and maintained within working memory, it cannot definitively be said that a memory was formed. The increase in performance resulting from the cue does suggest that the information is utilized, however an opposing view is that the performance differences are due to the simultaneous sensory information presentation. In this way, there is not necessarily a performance increase during unpaired trials relative to baseline as a result of the cued information, but a performance decrease relative to baseline as a result of paired multi-sensory information.

Many of these studies focus on the role of theta in explicit memory recall paradigms. Specifically, participants simply must report an item, retrieved from memory which can either be correct or incorrect. These tasks do not require any other behaviour other than simple button taps or speech. The present study highly differs from this approach by inducing a visuomotor performance test after stimulus onset whereby participants must respond accurately with a fast movement. This movement also requires a sensorimotor transformation manipulating a cursor onscreen with a mouse in the real world. As such, the data is less conclusive about the role of memory, especially post-stimulus onset. The sensorimotor challenge is also under considerable time pressure. As such, it is hard to differentiate the origin of the elevated pre-stimulus theta power between memory maintenance (in the unpaired condition) and motor action. However, the significant increase in pre-stimulus theta power present in the unpaired condition, could originate from participants propagating the information in their working memory. Future studies should systematically modulate this period with longer and short pre-stimulus multi-sensory cues that predict target direction, seeing if there is a continued propagation of information over longer time courses and if this effect has a shortest period. Furthermore, the duration of the cue could also be modulated to help reduce the load on working memory and, if the assumptions are correct, reduce theta power associated working memory.

Outcome Response

In the present study, feedback was delivered after each trial indicating whether the trial outcome was successful or failed. This brought about strong response, localized to frontal central regions. By computing failure minus success difference wave, a typical error related negativity plot was identified. In this plot, a strong negative deflection occurs 100ms after feedback onset switching to a strong positive deflection 300ms after feedback onset. Defined separately, successful trials produced a peak potential occurring earlier with a lower peak amplitude compared to errors. With erroneous responses the peak response occurred at 300ms after error onset. Although there weren’t any significant differences between skilled and unskilled players, this response is crucial to performance. Theta appears to coordinate the outcome response, especially to errors, shown by a drastic increase in theta power during outcome feedback. During errors, theta power was significantly higher compared to during success with similar amplitudes across both experimental conditions. As would be expected, the pairing of AV information does not influence the total power exhibited in feedback response. However, unexpectedly, pairing trials drastically increased the ERS of theta post outcome feedback. An explanation for this comes from the role of theta oscillations during error related feedback. Whilst theta might not necessarily provide motor adaptation drive (Janker et al., 2021), it is highly engaged during larger errors (Arrighi et al., 2016). It appears to inform participants about a need to change behavioural policy, something discovered across a wide range of experimental paradigms. In the present case, paired trial performance was significantly worse, therefore it is likely to assume that a greater degree of behavioural adaptation is required. As such, theta oscillatory power is higher in failed trials and show a greater synchronisation after errors. Theta absolute power is higher in skilled players compared to unskilled players as well as synchronisation, suggesting that behavioural adaptation is more prominent in unskilled players (van de Vijver et al., 2011). Although not explicitly measured in the present study, higher theta power is attributed to better learners (Cavanagh et al., 2010;). The skilled players group contains players who achieve a higher performance but crucially is made up of players who are both experienced and inexperienced with Esports. That is, the population consists of players who have learnt Esports over many hours of practice, and those who, despite being untrained, show an aptitude for the sport. Therefore, higher theta power in error feedback during the most complex visuomotor challenge condition, could result from players who are inducing a higher behavioural adaptation and predicted to be higher learners (Luft, et al., 2013).

Conclusion

The timing of audio-visual pairing considerably alters brain activity both pre and post visual stimulus onset. Providing a faithful directional cue improves performance provided there is temporal separation between cue and target onset times. This increases memory-associated neural oscillations that have a strong relationship to performance. Skilled players respond to this cue more strongly through a significant increase in anterior theta power which is strongly associated to faster reaction times. By pairing the audio-visual stimulation, a strong post-stimulus dipole with significant increases to frontal negativity and significant increases in posterior positivity, which is not present in unpaired trials. The difference in amplitude is significantly different in success trials than in failure trials of skilled players. As such, skilled players have been shown to utilize a sensory information, maintained in working memory by frontal theta power, to inform a faster response with significantly fewer errors and achieve a higher level of performance.

Chapter 6

Introduction

Esports has recently emerged as the world's fastest growing sport with worldwide participation at an amateur level, and global intrigue at a professional level. Organisations have emerged to bring together rosters of elite players, travelling the world to compete against the best for huge prize pools. At the highest level of competition, players sit at a computer and play their specific game competitively against opposing players, within the various formatting constraints of the sport. This high level of competition is conducted in a strikingly similar way to the standard approach within cognitive electrophysiology, making Esports an incredibly useful model to study brain activity, specifically, neural oscillations implicit in high performance within sport. Since the sport isn't played outside, in uncontrollable conditions, not containing physical contact with other players and doesn't require full body, high velocity movements, the data recorded is significantly less noisy than with other, traditional sports.

From a cognitive perspective, the challenge of Esports/VGs has been seen to induce enhancements important for daily life, but crucial for high performance in sport. For example, early-stage visual processing (Appelbaum et al., 2013), contrast sensitivity (Li et al., 2009), visual search (Castel et al., 2005) and top-down visual attention (Green and Bavelier, 2003). These visual processing enhancement effects are facilitated by larger central and peripheral field areas in VG players (Buckely et al., 2010). A crucial aspect of these studies is that the processes are all improved through training interventions with video game play including cognitive flexibility (Valls-Serrano et al., 2022), visual processing speed (Kowal et al., 2018) and visual working memory (Seya and Shinoda, 2016). Crucially, top-down attention is also enhanced through video-game play (Chisholmand and Kingstone, 2012). An important aspect of attaining a high-performance sport is training. Precise training interventions are used to improve motor skills, develop robust competition psychology, physical strength and fitness (Elliott and

Mester, 1998). Efficient and powerful performance can be achieved through repeated exposure to fundamental movements which, in turn, promotes coordination and appropriate activation (Cronin et al., 2001). Whilst this can be achieved in muscular-skeletal processes, it can also be applied to vision training, boosting perceptual performance (Knudson and Kluka, 1997).

It is important to note, that neuroimaging research on Esports is so far limited, however, more work has been done on video games (VG) play. Since Esports are a competitive format of video game play, the research is still appropriate here. Brain activity within Esports/VGs has so far focussed predominately on the role of theta frequency band, showing increases to frontal theta power during VG play compared to rest periods (Pellouchoud et al., 1999). Theta power increases as a function of rounds progressed and increases prior to the onset of feedback informing that a round has been successful (Sheikholeslami et al., 2007). In an older population, traditionally those who have a limited relationship with VGs but especially Esports, VG play has been shown to significantly increase theta power which was correlated to performance improvements on a plethora of cognitive tests (Anguera et al., 2013). By giving participants in two different age groups, young and old, a battery of cognitive tests, baseline performance could be calculated. The authors then used a VG intervention, challenging participants with a VG that harness precise movements and spatial tests to achieve a good score in the game. During this period, theta power increased, and subsequently correlated to an increase in performance on cognitive tests in the older population, who were inexperienced with VGs.

However, the neural oscillatory differences occurring between skilled and unskilled players during training exercises is poorly understood. The present study seeks to address that by using an aim-training software, called AimLabs, to test the performance of skilled and unskilled players during fundamental FPS aiming movement tasks. Both fundamental aiming movements implicit in FPS Esports will be used whilst brain activity is recorded through EEG. Whilst evoked, time-locked to stimulus onset, activity will be inaccessible through this methodology, induced neural oscillations during precise motor training will, for the first time, be quantified.

To probe the neural oscillations evoked by Esports play, a novel method was proposed using aiming training software AimLabs, concurrent EEG recording and eye-tracking. Aimlab is a commercial aim-trainer designed to improve performance in FPS Esports. It provides a collection of tasks and drills to challenge players in specific areas of aiming. Those can be the complexity of sensory information (large vs small targets, highly coloured vs dull targets, high numbers vs small numbers of targets, high vs low background contrast) and the complexity of the motor challenge (distances, sequence, motion). In most tasks, a time component is used of 60s, with players tasked with generating as high of a score as possible, within that time window. Score calculations can then be made adding points for hitting the target or remaining within the boundary of the target and removing points for missing the target or departing the boundary of the target. A streak multiplier is then applied for hitting multiple targets within succession or remaining within the target boundary for extended periods of time. As such, score is a function of accuracy over time. Unfortunately, due to AimLabs being a commercial company, there is exact computation used to generate score is not publicly known.

To test a wide range of aiming movements, two distinct studies using AimLabs were conducted. The first was, a study on flicking and the second was a study on tracking. These are the two fundamental aiming movements in FPS Esports that can be extrapolated to other Esports too, however they are most strongly induced by FPS. Flicking is a fast, reflexive single action movement that rapidly moves the mouse adjust the aiming location to the stationary target. Tracking is a slower continually updating movement that moves the mouse to follow a moving target. In Esports these movements are often chained together within a sequence, flicking to a target's location, and then tracking it as it moves. In this way, tasks were chosen that test the different aiming movements in a single action and continually updating way. In each study, participants played three different tasks on either flicking or tracking, depending on the study. Study one inducing flicking movements used the tasks: Gridshot, Spidershot and Burstflick. Study two inducing tracking movements used the tasks: Startrack, Switchtrack and Motiontrack. Below, each task parameters are described with their accompanying instructions written by AimLabs.

Methods

Participants

Two sets of participants were tested for this study. In the first 37 participants (15 Male, 12 Female) were used, 19 were classified as Skilled players and 18 were classified as unskilled players based on the methods described in the methods chapter. In the second, 42 participants (26 Male, 16 Female) took part of which , 23 were classified as Skilled players and 19 were classified as Unskilled players based on the methods described in the Methods chapter. Briefly, after reporting Esports playing time based on a self-report questionnaire, populations were determined based off Esports experience only. Players who played VG, whichever input modality, but not Esports were determined to be inexperienced. After completing various Esports and psychophysics tasks, their performance on these tasks was to perform k-means clustering and identify clusters of similarly performing player groups. Silhouette scores determined that two clusters were optimal and players were classified based on their cluster. Their previous experience was not included as part of the classification process. All participants were right-handed, didn’t wear glasses and had no history of neurological disorders. Crucially, all participants reported some experience with video-games.

Experimental Procedure

The experiments were programmed using Weblink stimulus presentation software (SR Research) to facilitate concurrent participant screen recording, eye-tracking and EEG recording. Each experiment is built modularly with the ability to send triggers from the stimulus pc to the eye-tracker host pc and EEG amplifier, synchronizing events in the experiment together. After introductory instructions regarding the use of AimLabs and eye-tracker calibration steps, participants would be provided with the same instructions reported above, written by AimLabs. From here the screen recording component would begin and a trigger denoting such would be sent. Participants would then load the experiment ‘custom playlist’ on AimLabs and complete the task. After completing the task and looking through the results which included information about task performance and ranking in both local and global leaderboards, participants would then receive instructions for the next task and proceed as described for the next set of tasks.

EEG recording and analysis

To identify game durations, a trigger was sent at the beginning of the video recording elements. This trigger was recorded in the message log of Weblink and could then be used to isolate the time in the video when the task began. By subtracting the offset between when the trigger was received by the eye-tracker, from the task start, this could serve as the initial crop point. Each task lasted for 60s, so the crop end time was calculated as the task start time + 60s. Each file was read in individually and cropped according to the trial start and end time.

The data was acquired using a 64-channel EEG (BioSemi) and processed using MNE – python toolbox, as described in Chapter 2. The data was subjected to a number of pre-processing and processing steps as outline in the methods chapter. Briefly, noisy sensors were first removed and interpolated by RANSAC algorithm. Then the data was downsampled to 200hz to reduce computation time. From here the data was passed through the AutoReject algorithm to reconstruct and drop extremely noisy epochs before being passed to the ICA algorithm which allowed for artefact detection and removal. Then the data was passed for a final time to AutoReject to reconstruct any remaining noisy epochs and drop any that still didn't pass the threshold (a lower threshold than the first AutoReject pass). At this point, the now clean data was filtered from 1-30Hz (high and low-pass) and average referenced.

With clean and pre-processed data, Morlet waveform analysis was applied to frequencies of interest. In this experiment, the frequency ranges used were Theta (4-7Hz), Alpha (8-12Hz), calculating individual frequencies in steps of 1Hz. To define the number of cycles, the frequency range was divided by 2 and fast Fourier transform was applied. The transformation was applied to the duration of each epoch which were created by making equally spaced epochs of a 1s duration. Power calculations per epoch could then be averaged together. In this way, the power estimates are induced rather than evoked (time-locked to events of interest).

Results

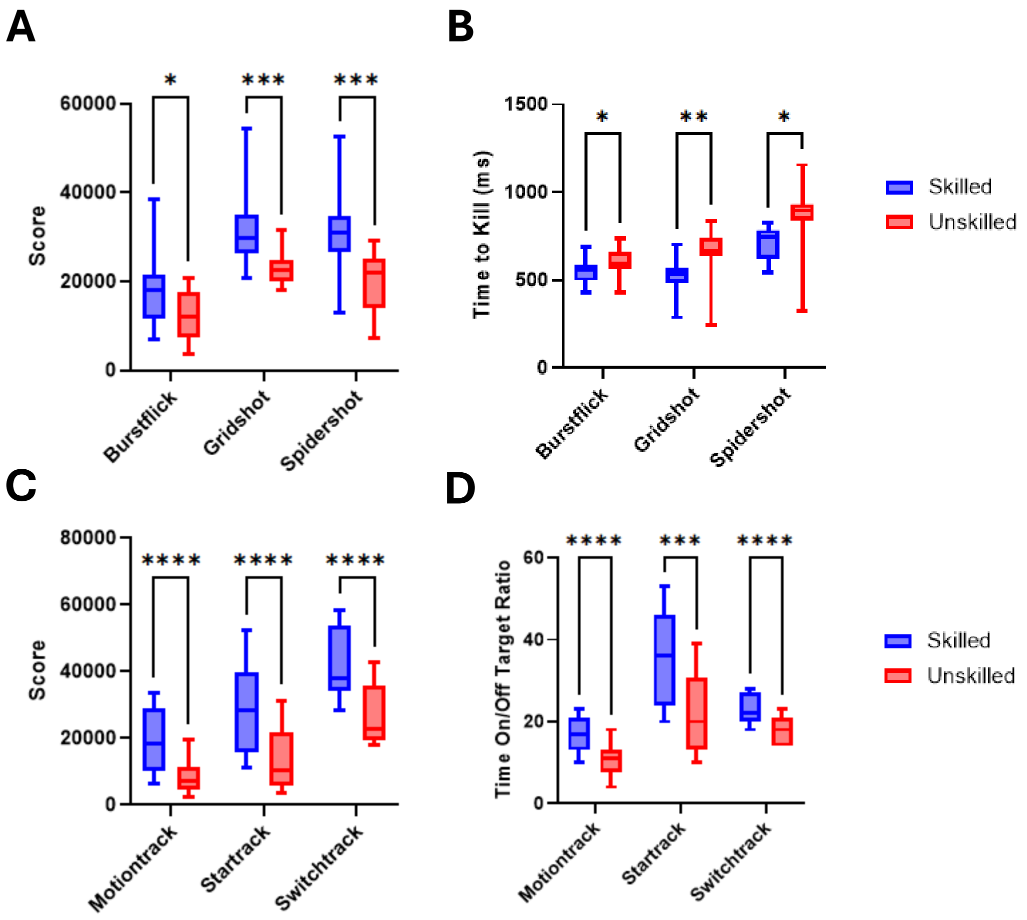


Figure 6.1. Behavioural performance results for AimLabs aim-training tasks divided into flicking and tracking experiments. A) Overall Score accumulated by participants across all flicking tasks across skilled and unskilled populations. B) Average Time to Kill of participants response across all flicking tasks across skilled and unskilled populations. C) Overall Score accumulated by participants across all tracking tasks across skilled and unskilled populations. D) Average time spent on/off target as a percentage ratio across all tracking tasks across skilled and unskilled populations.

Across the multiple tasks testing two different fundamental movements in Esports, flicking and tracking, skilled players perform significantly better than unskilled players. In flicking tasks, the interaction between task and population is significant for Score (F (2, 64) = 3.556, p = 0.0343). There was a significant score difference across each task (F

(1.059, 42.34) = 109.0, p = <0.0001) and across population (F (1, 40) = 16.55, p = 0.0002). Tukey's multiple comparison post-hoc test indicated there was a significantly higher score in skilled players across each task (Burstflick, p = <0.0115; Gridshot, p = 0.0001; Spidershot, p = 0.0001). Time to Kill also showed a significant interaction between task and population (F (2, 64) = 3.382, p = 0.0467). Differences across tasks (F (1.788, 57.21) = 58.57, p = <0.0001) and across populations (F (1, 32) = 11.16, p = 0.0021) were also significant. Tukey's multiple comparison post-hoc test indicated that there were significant differences in Time to Kill across all tasks (Burstflick, p = <0.0499; Gridshot, p = 0.0023; Spidershot, p = 0.0306). In tracking experiments there was a significant interaction between task and population is significant for Score (F(2,78) = 7.152, p = 0.0014). differences in score between task performance (F (1.925, 77.01) = 360.4, p = <0.0001) and between populations (F (1, 40) = 18.00, p = 0.0001) were also significant. Tukey's multiple comparison post-hoc test indicated a significantly higher score across all tasks in skilled players (Motiontrack, p = <0.0001, Startrack, p = <0.0001, Switchtrack, p = <0.0001). Finally, time on/off target ratio displayed a significant interaction between task and population is significant for Ratio (F(2,78) = 10.69, p < 0.0001). Significant differences between task (F (1.059, 42.34) = 109.0, p = <0.0001) and population (F (1, 40) = 16.55, p = 0.0002) were also found. Tukey's multiple comparison post-hoc test indicated higher time on/off target ratio across all tasks in skilled players (Motiontrack, p = <0.0001, Startrack, p = 0.0002, Switchtrack, p = 0.0003). With both movements, overall score from each task is significantly higher in skilled players. In the flicking tasks, the metric Time to Kill, determined as the time from target onset to its destruction, is significantly shorter in skilled players. In tracking the metric time on/off target ratio, the time spent within the target boundary relative to outside of it, is significantly higher in skilled players than unskilled players. Ultimately, the results show how skilled players perform significantly better than unskilled players by accumulating a higher score, accrued based on speed and accuracy, respond to targets significantly faster, and remain localized to the target for significantly longer.

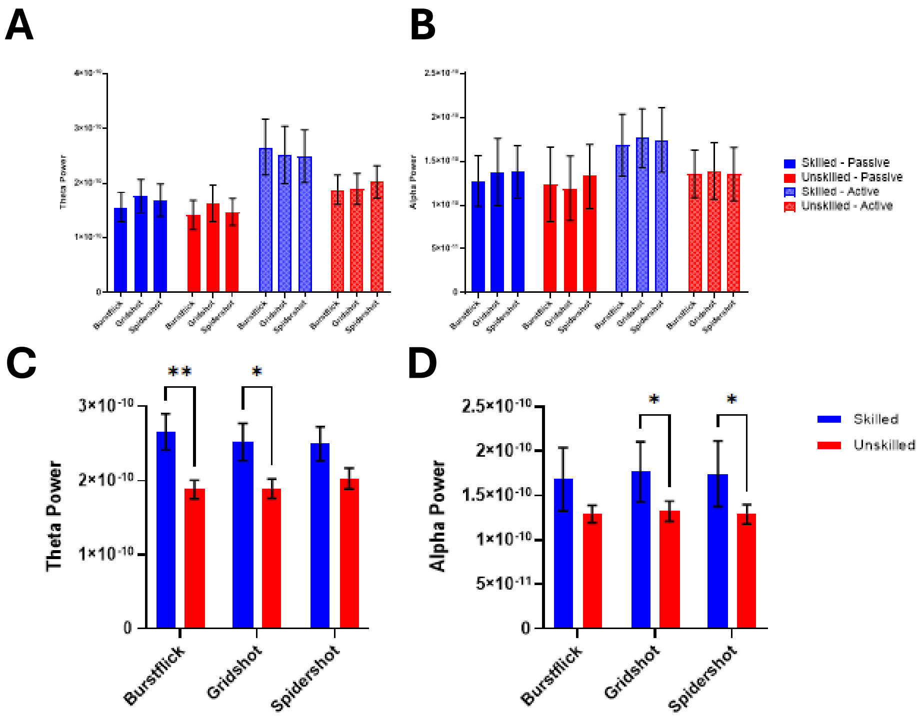


Figure 6.2. Oscillatory power changes during performance of flicking tasks in AimLabs. A) Theta power changes during passive and active portions experiments in frontal-central electrodes. B) Alpha power changes across tasks between passive and active portions of the experiment in occipital parietal electrodes. C) differences in theta power between skilled and unskilled players across the different tracking tasks. D) differences in alpha power between skilled and unskilled players across the different tracking tasks.

Frontal central theta power increased significantly in active conditions compared to passive conditions (F (0.9344, 29.90) = 36.87, p = <0.0001) but was not significantly different between participants (F (1, 32) = 3.373, p = 0.0756). By comparing both active and passive conditions and skilled and unskilled groups, a significant difference is revealed (F (1, 32) = 4.604, p = 0.0396). Occipital parietal alpha power significantly differed between active and passive conditions (F (0.9266, 29.65) = 5.522, p = 0.0278) but didn't significantly differ between populations (F (1, 32) = 1.365, p =0.2514). There wasn't a significant difference by comparing both active and passive conditions and skilled and unskilled groups (F (1, 32) = 1.630, p = 0.2109). In flicking tasks, there are significant differences between theta power levels across populations (F (1, 32) = 4.745, p = 0.0369) but not between tasks (F (1.901, 60.83) = 0.5502, p = 0.5709). Tukey's multiple comparison post-hoc test indicated significantly higher theta power in two tasks (Burstflick, p = 0.0086 and Gridshot, p = 0.035) but not in Spidershot (p = 0.0919). Occipital-parietal alpha power showed significant differences across population (F (1, 32) = 4.391, p = 0.0441) but not across task (F (1.845, 59.04) = 0.7792, p = 0.4540). Tukey's multiple comparison post-hoc test indicated significant increases in alpha power in skilled players in two tasks (Gridshot, p = 0.0316 and Spidershot, p = 0.0360) but not in Burstflick (p = 0.0536) although it was statistically trending. Whilst playing an Esports related aim-training task, frontal-central theta power increased significantly in the active conditions compared to the passive condition across both populations. Theta power also increased significantly in skilled players compared to unskilled players. The overall alpha power increased in active conditions compared to inactive conditions, although this effect was not significant and only present in skilled players. There are differences in the oscillatory power exhibited by skilled and unskilled players during the tracking experiments. Skilled players display significantly higher theta power across all tasks compared to unskilled players. Unskilled players show higher alpha power in the active tasks, but the result is not significant.

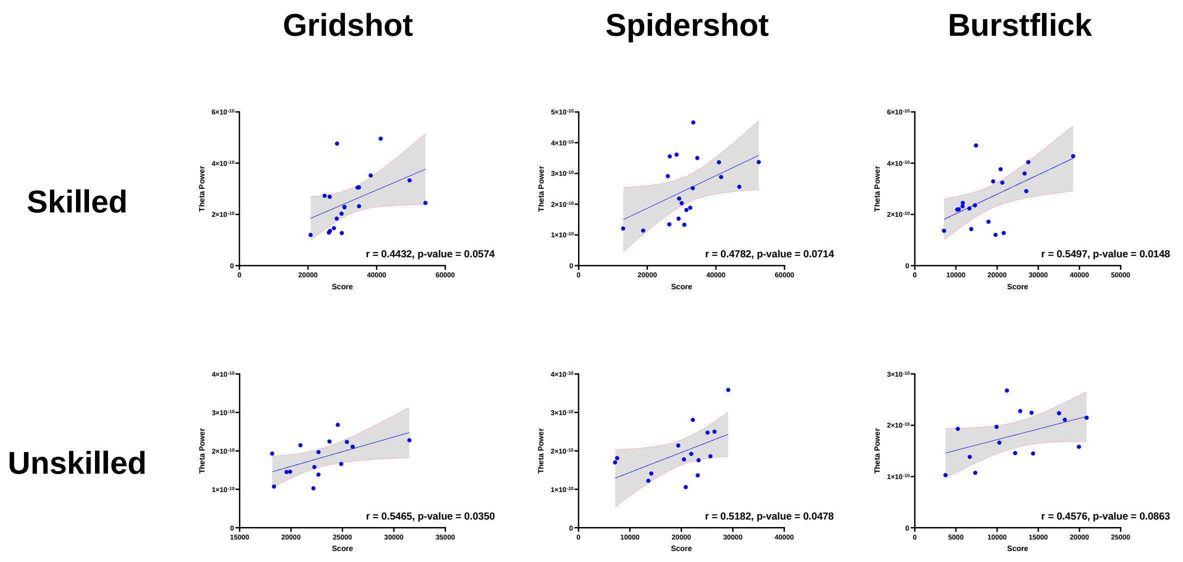


Figure 6.3. Correlations between theta power and score across each task in frontal-central sensors in flicking tasks.

Correlational analysis revealed significant positive relationship between behavioural performance within each task and theta power. In skilled players this relationship was significant for tasks: Gridshot, Spidershot and Burstflick. In unskilled players this relationship was strongly positive for Gridshot and Spidershot, but negative for Burstflick with no relationships being significant. In all cases, this slope of the GLM was drastically steeper in skilled players than unskilled players highlighting a much stronger relationship. In frontal central sensors, there is a significantly stronger relationship between theta power and performance, presenting theta power as a indicator of performance in skilled players but not unskilled players. However, by using Fisher's r-to-z approach, there were no significant differences across all correlations (Gridshot: z = 0.359, p = 0.36; Spidershot z = -0.139, p = 0.445; Burstflick: z = 0.324, p = 0.373).

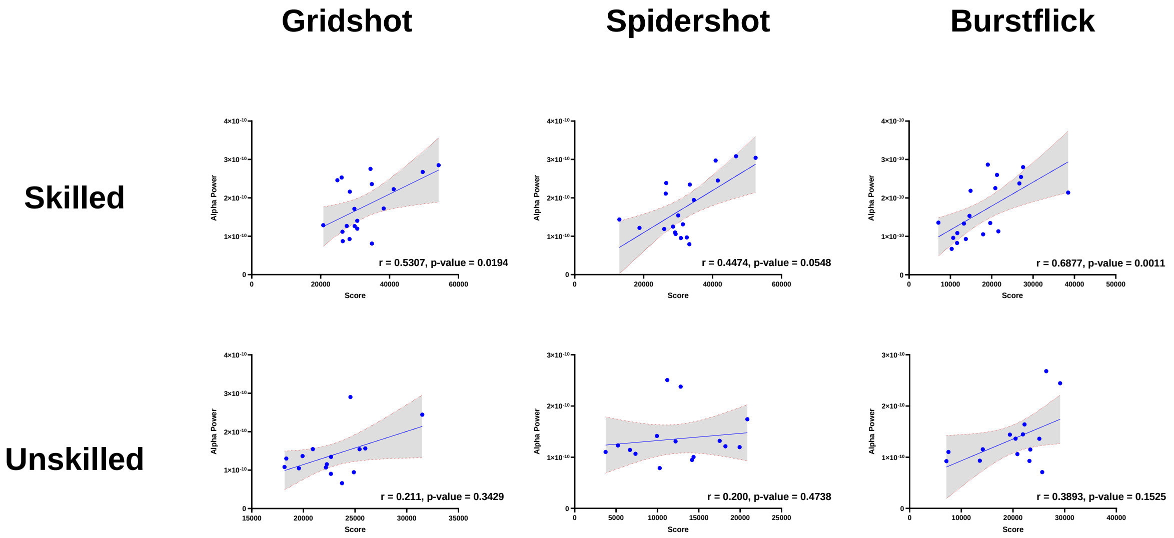


Figure 6.4. Correlational analysis between occipital-parietal alpha power and performance across skilled and unskilled players in each flicking task.

Alpha power is shown to be correlated strong to performance in skilled players be not in unskilled players. In skilled players, a significant positive correlation is found in the Gridshot and Burstflick tasks and a strong positive correlation is found in Spidershot. In unskilled players, the relationship between alpha power and performance is much weaker, shown by insignificant p-values and smaller correlation coefficients. The strongest relationship is with the Burstflick task, with Gridshot and Spidershot being much weaker (shown by a smaller r value). None of these relationships are significant. Across all players, alpha power seems somewhat correlated to performance, with a stronger correlation in skilled players. However, by using Fisher's r-to-z approach, there were no significant differences across all skilled vs unskilled correlations (Gridshot: z = 0.612, p = 0.27; Spidershot z = -0.087, p = 0.465; Burstflick: z = 1.133, p = 0.129).

Tracking

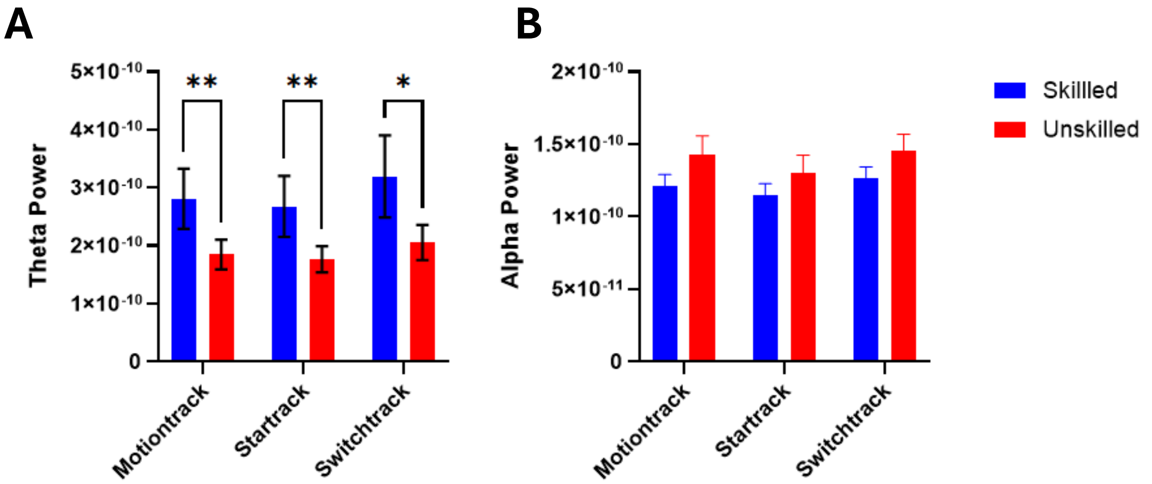


Figure 6.5. Oscillatory power changes during performance of flicking tasks in AimLabs. A) Induced theta power changes across all flicking tasks across both populations. B) Induced alpha power changes across all flicking tasks across both populations.

During tracking experiments, theta power was significantly higher in skilled players compared to unskilled players. There was a significant interaction between population and task in frontal central theta during tracking tasks (F(2, 76) = 8.79, p = 0.0185).There was a significant difference across tasks (F (1.855, 70.48) = 20.50, p = <0.0001) and across populations (F (1, 38) = 9.521, p = 0.0038). Tukey's multiple comparison post-hoc test indicated significant differences in theta power in skilled players across all tasks (Motiontrack, p = 0.0016; Startrack, p = 0.0026 and Switchtrack, p = 0.0044). Occipital parietal alpha power showed no significant interaction effect between population and task (F(2, 76) = 0.3134, p = 0.7319). There were also no significant differences between populations (F (1, 38) = 0.7573, p = 0.3896) or across the tasks (F (1.893, 71.92) = 1.794, p = 0.1755). During tracking tasks, skilled players showed significantly higher frontal-central theta power compared to unskilled players.

However, alpha power was higher in unskilled players across all tasks but showed no significant differences.

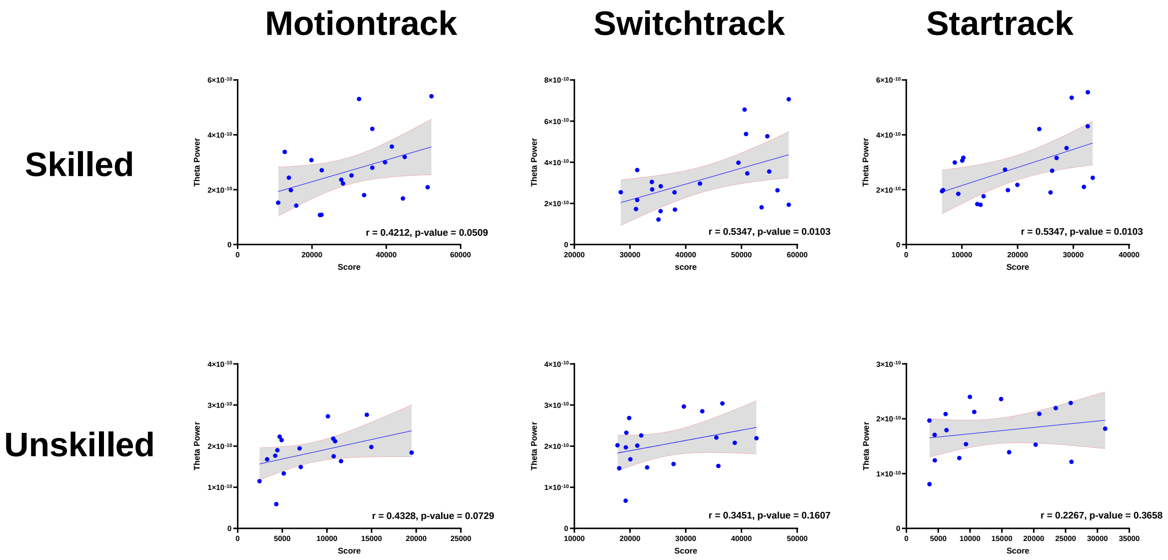


Figure 6.6. Correlations of theta power and performance across both skilled and unskilled populations in tracking tasks.

Across all populations, theta power is positively correlated to performance. In skilled players significant correlations are found across Switchtrack and Startrack tasks, and a strong correlation is found in Motiontrack. In unskilled players, strong correlations are found in Motiontrack and Switchtrack tasks, and a weak correlation is found in Startrack. None of these correlations are significant. However, by using Fisher's r-to-z approach to compare correlations, there were no significant differences across all skilled versus unskilled correlations (Motiontrack: z = -0.041, p = 0.484; Switchtrack: z = 0.722, p = 0.235; Starttrack: z = 0.905, p = 0.183).

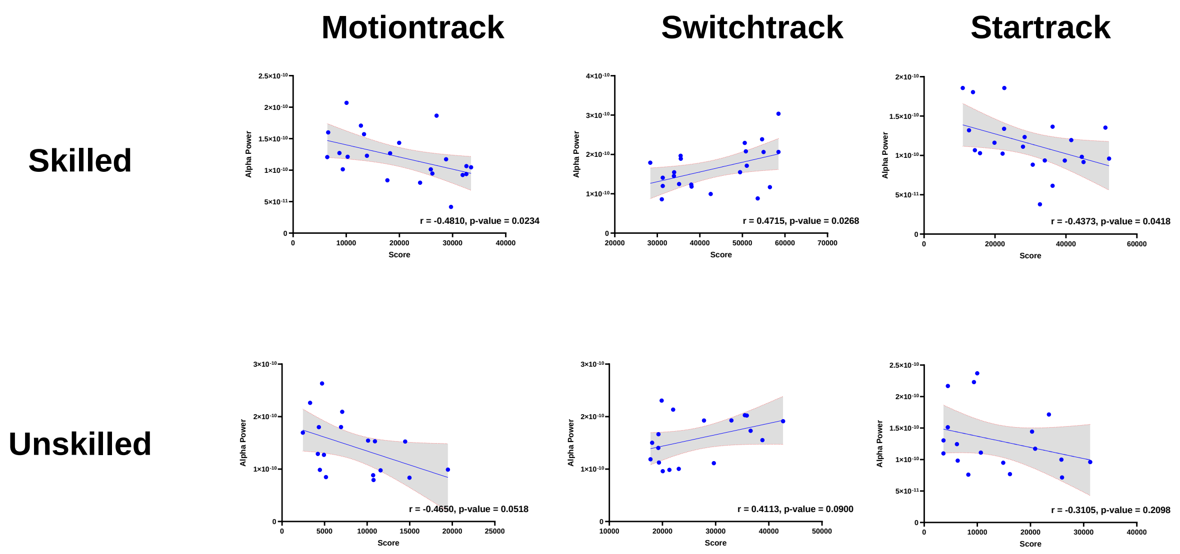


Figure 6.7. Correlations of occipital parietal alpha power and performance in tracking tasks.

In both skilled and unskilled players, there is a negative correlation between alpha power and performance in the Motiontrack and Startrack tasks, and a positive correlation in Startrack. In skilled players, the relationship is significant for every task. In unskilled players, there is no significant relationships, although there are strong negative correlations in the Motiontrack and Startrack tasks. By using Fisher's r-to-z approach to compare correlations, there were no significant differences across all skilled versus unskilled correlations (Motiontrack: z = 0.015, p = 0.494; Switchtrack: z = 0.217, p = 0.414; Startrack: z = -0.428, p = 0.334).

Discussion

The present study seeks to apply cognitive electrophysiological techniques to sport science data, overcoming logistical challenges in common practices whilst retaining ecological sporting validity. To that end, an ecologically valid methodology was employed by capturing participant performance on aim-training tasks within the commercial aim-training software, AimLab. The tasks used induced fundamental movements required by FPS Esports in a high-volume, fast-movement paradigm. In some tasks (Gridshot, Spidershot, Switchtrack) multiple targets were always present on the screen, with participants freely choosing which one to shoot at first, before switching to the next. In the remaining tasks, only a single target was present. Skilled players performed significantly better than unskilled players across all behavioural metrics across many tasks. Time to kill (TTK) and time on/off target ratio (TR), two time dependent but accuracy irrelevant metrics, produced significant differences in performance between the two populations, with a significantly shorter TTK and a significantly higher TR in skilled players. Score, a combination of speed and accuracy, which accumulated throughout the trial resulting from successful shots and amplified by consecutive successes, displayed the strongest significant differences between the populations. Skilled players accumulated a significantly higher score than unskilled players across all tasks.

Two experimental conditions were used in the first study, comparing active and passive conditions on the same AimLab task. In passive conditions, participants would watch a video of a professional player complete the same task before playing it themselves. It served to solidify instructions and display the movement speed required to achieve a high score. In active conditions, players would then take part in the task, implementing what they had just observed. Theta power was significantly higher in active conditions compared to passive conditions in frontal-central sensors and alpha power was higher in occipital-parietal sensors however this effect was only present in skilled players. There were no significant differences found in neural oscillations between populations in the passive condition.

Theta power in frontal-central sensors was higher in skilled players across both fundamental aiming movements, flicking and tracking. Through correlational analysis, a positive relationship was discovered between theta power and performance, with high power being associated with high scores in skilled players. Although this relationship was directionally the same in unskilled players, the relationship was not significant but was trending in certain tasks. Alpha power was found to be significantly higher in occipital parietal electrodes in skilled players in the flicking experiments, but lower in the tracking tasks, although this effect was not significant. There were no significant differences in alpha power found in unskilled players. Correlational analysis revealed significant relationships between alpha power and performance but in opposite directions in skilled players. In the flicking experiment, a strong, positive and significant relationship, showing high power and high performance, was found. However, in the tracking experiment, a strong, significant, negative relationship, showing low power and high performance, was found. There were no significant relationships found in unskilled players in the flicking experiment, which showed weak correlations, but strong negative relationships were found in the tracking experiments, some being significant, between low power and high performance. As such, the present study finds that in skilled players frontal-centrally distributed theta power is a strong indicator of performance across all fundamental aiming movements in Esports, but alpha power might be modulated by the required movement, either flicking or tracking.

The increased theta power observed in both participant populations was localized to the frontal midline of the cortex. The observed theta pattern is associated with activity in the anterior cingulate cortex (ACC) and prefrontal cortex in source localization studies (Onton et al., 2005; Ishii et al., 2014). Theta power localized to the ACC and other frontal structures has a diverse range of functions in complex cognition such as action regulation (Luu and Pedersen, 2004) and monitoring (Cavanagh et al., 2009); conflict monitoring (Botvinick et al., 2004), task selection (Womelsdorf et al., 2010). Theta power is also highly prevalent in the hippocampus and its thus strongly associated to elements of memory (O'Keefe and Reecee, 1993; Buzsáki, 2005). In particular, retention (Jensen and Tesche, 2002) and encoding (White et al., 2010). However, the present study observes theta power during a highly complex and dynamic visuomotor task. The ACC has strong connections to the motor system (Deiber et al., 1999) and parts of the ACC have been shown to play an essential role in the preparation and readiness (Cunnington et al., 2003), planning (Jankowski et al., 2009) and initiation (Hoffstaedter et al., 2013) of intentional movements. The present study induces a highly complex array of movements required precise motor control, speed and accuracy within a very quick succession. The extreme temporal density of movements and the precision requirements of them, go far to explain the upregulation of theta power in both populations.

Other studies have linked to video-game play to increases in theta power (Pellouchoud et al., 1999) with increases compared to rest periods. The relative power of theta also increases as, time spent playing video games increases or as rounds progress (Sheikholeslami et al., 2007). Theta increases have been shown during violent events in other FPS video games (Salminen and Ravaja, 2008) which required the execution of an aiming movement to hit the opponent. Importantly, training in older populations, induces significant increases to theta power that are sustained for long periods and are associated with other cognitive test improvements (Anguera et al., 2013). Crucially, the older population of participants were inexperienced with video games and the associated increases in theta were because of video-game play. This highlights the interesting cognitive challenge of Esports since they require drastic sensorimotor transformation to the virtual world where movements on the screen mismatch the movements in the real world. For example, moving aim location vertically requires participants to move horizontally in the real world. This is an unusual, non-natural movement and might test the ability of players to adapt. The network required for this type of process is explicitly activated by mouse manipulation (Gorbert et al., 2004), the key movement in Esports aiming. As such, it appears that complex aiming movements, required in Esports, activate a cortical network of prefrontal and premotor cortices, coordinated by theta power. This network operates differently as a function of skill level, with higher skilled, better performing players showing greater activation. Enhancements to a variety of cognitive abilities of players are commonly associated with video game play including cognitive flexibility (Valls-Serrano et al., 2022), visual processing speed (Kowal et al., 2018) and visual working memory (Seya and Shinoda, 2016). Crucially, top-down attention is also enhanced through video-game play (Chisholmand Kingstone, 2012,

However, theta band activity is also linked to cognitive control, signalling an increase in demand (Cavanagh and Frank, 2014). In this view, it explains the lack of significant differences in theta bands due to the complex computations required for high performance in the tasks. Not only is a high level of attention required, but cognitive and motor control. Both populations are under extreme cognitive load due to the intensity of tasks, speed of movements required, visual complexity and time-pressure.

Related to this, displaying how theta is sensitive to complex events in videogames. In this way, theta differences could be resulting from a mixture of cognitive mechanisms that aren't possible to disseminate from this set of results alone.

A key finding within cognitive performance tests in video game players is the ability to task switch (Boot et al., 2008), an effect broadly coordinated by attention. Within the neuroscience literature, task switching is commonly associated with a suppression of alpha power and event related desynchronisation in the alpha frequency band prior to movement onset. In the flicking experiments, participants must switch between a multitude of competing targets rapidly but also accurately. One would assume based on the strong field of research on posterior alpha power desynchronisation prior to task switching (Verstraeten and Cluydts, 2002. Sauseng et al., 2006), that these tasks would be associated with decreased alpha power and an inverse relationship to performance would be found. However, the opposite is true. In tasks where there is a high prevalence of switching between tasks, there is a significant, positive relationship to performance. This is predominantly found in the flicking tasks however, the same is true for the tracking tasks, Switchtrack, that – as the name implies – requires switching between targets racking and tracking them as they move.

There are several possible explanations here for this result. Firstly, the literature on task switching using event locked methodologies, whereby decreases in posterior alpha are pre-stimulus presentation, which in turn predicts task switching. Also, this switch is voluntary, not determined by a performance variable. In the present study, participants must switch target once it has been 'destroyed' either by shooting it or remaining within its boundary for a certain period. As such it is not a voluntary switch, but determined by what is required by the task. Secondly, the tasks that involve switching are associated with additional targets present on screen at any one time, or that are followed incredibly quickly based on performance or time. In Gridshot and Switchtrack there are up to 9 targets on screen at any one time and in Spidershot and Burstflick, targets appear sequentially immediate after being destroyed or after a 200ms time window is over. This is to accurately mimic ecologically valid Esports aiming scenarios where multiple targets are presented at one time, or incredibly close together.

As such, the observed power increases in alpha, with respect to single target conditions, and their significant positive relationships to performance, might in fact reflect increases in attention to inhibit distractor influences (e.g. alternative targets) and focus attention on the present stimulus. This is well documented in the literature. (Benedek et al., 2014). Furthermore, alpha power has been shown to decrease in response to moving images but increase in response to still (Simons et al., 2003). Although this doesn't fully explain the present data, it offers some explanation for why single, moving objects displayed decreases in alpha power in compared to multiple static ones. In this view, it appears that the increase of alpha power in skilled players reflects decreases in attention to non-salient targets. It is possible that the decreased alpha power in the tracking conditions is a result of continually updating the aiming location and it in and of itself, switching.

Unfortunately, with the methodology employed, limited by the constraints of using a commercial aim-trainer, event related dynamics are not possible to isolate. Nor is any time-frequency decomposition. Future studies should focus on this difference by creating multi-target, complex movement tasks, that incorporate both static and moving targets trials, single and multi-target trials signalled by a trigger system.

Conclusion

During the performance of high frequency, complex fundamental Esports related movements, vast differences occur between skilled and unskilled players. Skilled players show a significant increase in score across all aiming tasks, incorporating both tracking and flicking movements. These individual movements are intrinsic to performance in Esports competition are tested here in a controlled and ecologically valid way. AimLabs functions as an aim-training software, commercially available but used by professional players to precisely train aspects of these movements, notably the speed and accuracy. In the present study, the enhanced performance of skilled players appears to be coordinated by frontal theta power emerging from frontal-central regions, presumed to emanate from the anterior cingulate cortex. Theta power, across both populations, is significantly higher in active versus passive conditions, something consistent with the literature. The higher frontal theta power is associated with increased performance, with strong associations in skilled players than unskilled players. Furthermore, alpha power in occipital-parietal regions also appears to play a key role, although differently depending on the task demands. In tasks requiring large amounts of switching between tasks, there are increases in alpha power and a strong inverse relationship between alpha power and performance. In tasks where a single target is tracked, a significant positive relationship occurs. These relationships are stronger in skilled players. As such, skilled players appear to achieve a higher performance due to an increase in theta power emanating from the ACC which improves the speed and accuracy of motor output and differentially modulate alpha coordinated attention depending on the nature of the targets used, preferentially increasing alpha in multi-target switching tasks, and decreasing in single target tracking tasks, potentially reflecting an increased ability to actively suppress distractors.

Summary

To conclude the present thesis sought to address the role of brain activity in the execution of precise movements to identify neural correlates of high performance. Skilled players display a higher level of performance that can be captured through a variety of tasks that directly test fundamental movements in Esports. As with many sports, high performance in Esports has two important factors, speed, and accuracy. Better performing players routinely display faster and more accurate movements. Combining metrics from a variety of tasks allows for the creation of two groups, skilled and unskilled, regardless of prior sporting experience.

Skilled players display an enhanced performance level, in part, due to their visual system accessing task-dependent visual information for future use. There appears to be a brain activity profile reflecting high performance within the time domain of electrophysiological data. Skilled players more readily display reduced VAN latency and increased p300 amplitude. This response, evoked by visual information is displayed more readily in skilled players and facilitates enhanced visual perception and task-related conscious access to the available sensory information. Another neural correlate of high performance is lower pre stimulus alpha power that amplifies visual awareness. In skilled players, further reductions in alpha power are observed potentially facilitating the readiness of an enhanced visual response. Disengagement of attentional resources is a potential substrate for athlete training. Furthermore, appropriate management of cognitive load is implicated shown by reduced theta power appears to be crucial to execute an appropriate response. Therefore, moderations to cognitive control were important for high performance. It is possible that unsuccessful trials induced inappropriately large signalling for control that impinged performance in skilled players. By pairing sensory information, it has been shown how skilled players are able to utilize a sensory information, maintained in working memory by frontal theta power, to inform a faster response with significantly fewer errors and achieve a higher level of performance. Despite multi-sensory information perturbing neural processing, skilled players still display increased visual awareness. Skilled players display an enhanced reaction to errors displayed by increased theta power and theta ERSP, displaying a strong role for negative reinforcement learning for high performance.

When presented with the most complex tasks requiring repeated, fast and accurate movements, skilled players display increases to frontal midline theta which strongly correlates to performance. Across all tasks, theta is significantly higher in skilled players, a stark contrast to the psychophysics tasks where unskilled players display higher power across all frequency bands. The upregulation of theta power seems to relate to the increased cognitive challenge caused by Esports, managing cognitive load to facilitate a high level of performance.

Future research

The present thesis utilizes the inherent advantages of using Esports as a model for sport neuroscience in a way that has never previously been achieved. It highlights how Esports and skilled Esports players display a greatly enhanced performance level that is correlated strongly to various aspects of their brain activity. However, further research should focus on neural correlates during the most demanding tasks. The literature is saturated with psychophysics tasks testing a wide variety of cognitive processes. However, the complex nature of Esports, on visual processing and motor responses, is rare. Isolating small elements of cognition might not continue to yield results in the same way as the past. Esports presents a unique opportunity to manipulate complex cognition within the framework of sport, something previously thought impossible. A key advancement would be to isolate evoked brain activity, as opposed to induced (measured in the present thesis). In this way, time-frequency representations of power could be utilized to further isolate how the brains of high skilled players differ from unskilled players. The visual complexity of Esports provides such a novel sensory environment that pushes visual processing to the extreme. Further isolating how this system responds could be a very fruitful avenue.

Applied implications

An important aspect of the present thesis is relating brain activity to performance using the conceptual framework of sport. As such, understanding how this research could be utilized by both athletes and coaches is important. Crucially, this thesis is useful not just for Esports, the sport used throughout, it can also act as a model sport with transferrable results to any sport relying heavily on rapid sensory processing and precise movements. Since the thesis primarily uses Esports as the framework for sporting performance, Esports athletes and coaches will be able to directly use the data to address performance issues. However, this thesis serves as a blueprint for detecting performance in sensory information driven, fast and precise movements for a wide variety of sports.

A key finding of the thesis is that early-stage visual processing pre and post stimulus onset, directly contributes to the execution of a precise mouse movement. Esports athletes are repeatedly executing this type of movement throughout each game. Yet, this process is implicated in a wide variety of sports too. For example, racket sports such as tennis and badminton, batting sports such as cricket, ball sports such as football and rugby, combat sports such as boxing and MMA. All these sports require very fast visual information processing of target location. It doesn't matter whether the target is a ball, a limb or an opponent, sports where visual perception is an integral component that drives a motor response will greatly benefit from understanding this research. Therefore, coaches could measure their players brain activity and identify if these components are lacking. It may be that before a stimulus onset, they display high levels of alpha power or, post stimulus onset, they display reduced amplitude of p100 and p300 components. As such, a training intervention could be used to improve these important biomarkers of performance.

In general, there are two predominant ways it can be used for athletes of Esports and other sports, identifying sensory processing weaknesses and training the responses. Identifying weaknesses with the very early phases of visual processing, could be a key indicator that a player has a weakness in this area. This process is so integral to many sports and thus the approaches to identify differences across players in an elite squad could benefit them in the future. Although training interventions to modulate time domain components are not well established except through behavioural training, neural oscillations can be modulated through neurofeedback. Through neurofeedback training, it would be possible to reduce alpha oscillations pre stimulus onset. Together with sport-specific coaching, the athlete can implement the feedback training midgame to improve performance. Furthermore, younger players, those on a pathway to becoming professional could be tested as a means of predicting their future potential. We do not know if it is possible to boost early time domain components such as p100, VAN and p300 and if that will improve performance directly. Therefore, identifying athletes with these traits that are either innate or, more likely, been developed over their early years, could greatly improve the accuracy of identifying future elite players.

The tasks used within this thesis could easily be adapted or changed to include more sport specific information but in their current form could provide benefit to a wide variety of players, boosting their cognitive control, information processing and movement execution.

Limitations

There are three general principles of limitations within this thesis that will be explained below. These are: limitations with EEG, limitations with Esports as a model for all sport and limitations of the task ecological validity with Esports.

The neuroimaging technique of EEG is limited by the nature of the signal itself, what is recorded and how the voltage is detected in the brain. Fundamentally there are a few different issues. Firstly, activity recorded at the scalp and at a single electrode is not only from activity directly underneath the electrode. In other words, there is a large amount of signal mixing across electrode sites, emanating from a larger radius of the cortex than denoted by the electrode. This makes deciphering what the voltage recorded at a specific site more difficult. In the present thesis, this limitation has been mitigated by averaging the activity from multiple electrodes. Secondly, EEG can only record from activity at the cortex level. This means that many crucial areas of the brain, implicated in a plethora of cognitive processes are inaccessible for this type of research. In the present study, certain parts of the thesis would have been greatly benefited from having activity from regions such as the hippocampus or the basal ganglia, unfortunately this is not possible. in some way this could make the brain activity seem incomplete, but in truth, there isn’t a single modality where the entirety of information mined from the brain could be accessed. fMRI, MEG, OPM all have resolution issues, in the same way that EEG has. For the present thesis, restrictions to cortical areas did not present a drastic issue since the main focuses were the visual cortex, motor cortex and the frontal cortex, all of these being cortical sites and well-established targets in the literature.

Another limitation in the present study was the use of Esports as a model for all sport. With more traditional forms of sport (such as football, athletics, tennis) the physical aspect of the sport is a crucial aspect. How one functions under extreme physical stress and exhaustion is a key concept in Sport Neuroscience. Esports, unlike these sports, does not have the same physical exertion requirements. However, that does not mean the physical demands of the movement aren't extreme. Although not under heavy load or exerting extreme force, the movements are incredibly precise, fast and are responding to minute visual changes in mere milliseconds. As such, the dynamic nature of Esports and the complexity of the sport make the cognitive demands on par with any sport out there. If a sport was defined purely on its physical demands, then some of the world's greatest sports wouldn't be classified as such for example, golf, cricket or snooker.

Finally, the tasks themselves are not directly Esports, only Esports-related. Although a fair comment, the tasks used in this thesis are directly testing Esports-related movements. They are fundamental to how Esports is performed. An unfortunate limitation of the experiments is not directly extracting brain activity from an Epsorts match directly. This was primarily due to the inability to send triggers from in game events. Code within Esports games, commercially build and sold video-games, is not easily manipulated. As such, building a functioning trigger system that fired based on in game events marking important moments, was beyond the computing capabilities of the authors. Furthermore, the behavioural metrics of reaction time and errors used in the psychophysics task may be limited in certain ways, but they are the key concepts in Esports, fundamental performance and they can be extrapolated to performance in other sports too.

Ultimately, the present thesis is not bereft of its own limitations, but various steps have been taken to mitigate these issues. Specifically, focusing on neural correlates from cortical sites that have been averaged over numerous electrodes, using a model sport that requires complex cognition and fast precise movements as expected in most traditional sports and finally, using tasks that probe the fundamental movement in Esports in a targeted and scientific manner.

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