

EEG Based Correlates of Attention in Intracortical Brain Computer Interfaces

by

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BS. in Biomedical Engineering, New Jersey Institute of Technology, 2022

Submitted to the Graduate Faculty of the
Swanson School of Engineering in partial fulfillment
of the requirements for the degree of
Master of Science in Bioengineering

University of Pittsburgh

2024

UNIVERSITY OF PITTSBURGH

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Intracortical brain-computer interfaces (iBCIs) exhibit variable performance across and even within days. A limited number of studies have shown that attention is one factor which can affect performance, but these have primarily looked at EEG-BCI and utilized simplistic tasks which may underestimate the true attentional load real-world BCI users may face. To further examine the impact of attentional load on BCI performance and the motor signal which drives it, we utilized a complex 2D computer cursor translation + click iBCI task paired with an N-Back (N=1,2) task to induce attentional load. We used EEG to quantify attention with theta and alpha band frequency power. We found that performance remained stable across conditions for both participants (P2 and P4). For the most challenging dual-tasking condition, the participants overall firing rate increased, potentially as a compensatory mechanism to maintain performance. P4 displayed changes in theta during the hardest dual-tasking condition but with no changes in performance or the neural motor signal. When we examined the effect of increases in neural correlates of attention on performance and the motor signal of each trial, combined across single- and dual-tasking, in a multi-variate regression, we found P2 exhibited decreases in performance and degradation of the motor signal. P4's performance improved instead, despite similar degradations of most motor signal metrics. These subject specific effects may be due to P4's higher baseline performance as a result of his newer implant allowing greater control that is less

vulnerable to attentional load. Overall, the effects of attention in iBCI performance were small, indicating the robustness of iBCI to high attentional load. We were also able to measure attentional changes through EEG during simultaneous intracortical recording. This lays the groundwork for future studies that wish to take advantage of a dual-modality setup in humans.

Table of Contents

| | |
|---|-----------|
| 1.0 Introduction..... | 1 |
| 1.1 Brain-Computer Interfaces | 3 |
| 1.2 Brain-Computer Interface Performance Variability | 6 |
| 1.3 Theories and Functions of Attention | 10 |
| 1.4 Attention in Brain Computer Interfaces | 14 |
| 1.5 Goals, Aims, & Innovation | 16 |
| 2.0 Approach | 18 |
| 2.1 Overview..... | 18 |
| 2.2 Study Participants | 18 |
| 2.3 BCI Calibration | 19 |
| 2.4 BCI and N-Back Task | 19 |
| 2.5 Session Design | 21 |
| 2.6 EEG Processing | 22 |
| 2.7 Intracortical Data Processing..... | 25 |
| 3.0 Effects of Attentional Load on Performance..... | 27 |
| 3.1 Introduction | 27 |

| | |
|---|-----------|
| 3.2 Methods | 28 |
| 3.3 Results..... | 29 |
| 3.4 Discussion | 38 |
| 3.4.1 Attention Change as Attentional Load Increases..... | 38 |
| 3.4.2 Why Does Alpha Power Increase..... | 39 |
| 3.4.3 Performance is Robust to Attentional Load | 40 |
| 3.4.4 Attention-Performance Relationships..... | 41 |
| 4.0 Effects of Attentional Load on the Motor Signal | 43 |
| 4.1 Introduction | 43 |
| 4.2 Methods | 44 |
| 4.3 Results..... | 44 |
| 4.4 Discussion | 49 |
| 4.4.1 Movement-Related Activity Remained Stable under Attentional Load | 49 |
| 4.4.2 Attention Metrics Exhibit Complex Relationships with Individual Motor Signal Metrics | 50 |
| 5.0 Summary and Conclusions | 52 |
| 5.1 Impact..... | 52 |
| 5.2 Limitations and Future Work | 53 |
| Bibliography | 55 |

List of Tables

| | |
|--|-----------|
| Table 1 EEG Sample Size..... | 24 |
| Table 2 P2 Alpha Power vs Performance Regression..... | 35 |
| Table 3 P4 Theta Power vs Performance Regression | 35 |
| Table 4 P4 Alpha Power vs Performance Regression..... | 36 |
| Table 5 P2 Theta Power vs Motor Signal Regression..... | 46 |
| Table 6 P2 Alpha Power vs Motor Signal Regression | 46 |
| Table 7 P4 Theta Power vs Motor Signal Regression..... | 47 |
| Table 8 P4 Alpha Power vs Motor Signal Regression | 47 |

List of Figures

| | |
|---|-----------|
| Figure 1 University of Pittsburgh iBCI..... | 3 |
| Figure 2 Decoder Quality across Time..... | 8 |
| Figure 3 BCI Task..... | 20 |
| Figure 4: Session Flow | 22 |
| Figure 5 EEG and Intracortical Array Placement | 23 |
| Figure 6 EEG Sensorimotor Rhythm Desynchronization..... | 24 |
| Figure 7 iBCI Performance Metrics..... | 30 |
| Figure 8 N-Back Accuracy | 31 |
| Figure 9 Mental Effort Scores | 32 |
| Figure 10 Attention Metrics..... | 33 |
| Figure 11 N-Back Only Attention Metrics..... | 34 |
| Figure 12 Attention & Performance Scatter Plots..... | 38 |
| Figure 13 Motor Signal Metrics..... | 45 |
| Figure 14 Attention & Motor Signal Scatter Plots | 48 |

Preface

Acknowledgements:

Many thanks to the Rehab Neural Engineering Labs (RNEL), particularly the BCI motor team and engineering team, and our participants, Nathan and Phil, for making this work possible. I would also like to thank Chloe Shearer for her aid in planning and interpreting the statistical analyses. Finally, I would like to thank my committee members and research advisor for guiding me through this project.

Funding:

This work was funded by an R01 from the NIH (R01NS121079) under Dr. Jennifer L. Collinger and a fellowship from the DOD (#HQ00342110020) for the Pitt/CMU BRIDGE program.

1.0 Introduction

Traumatic injury or disease can lead to paralysis or impairments that can limit a person's ability to interact with their environment. Unfortunately, many people experience these types of injuries that can have a significant impact on independence and quality of life. For example, roughly .2-40 out of 10,000 people per year will experience an upper limb amputation (Kwah et al., 2019). There are about 18,000 new traumatic spinal cord injury incidents per year, with roughly 59.7% resulting in incomplete or complete tetraplegia (*Traumatic Spinal Cord Injury Facts and Figures at a Glance*, 2024). 2-25 per thousand people suffer from strokes every year, many of whom experience motor or communication impairments (Wolfe, 2000). These different patient populations are all in need of tools which can aid them after injury. Brain computer interfaces (BCIs) are on such tool that provide the opportunity to restore agency and independence to those with paralysis or missing limbs by allowing control of a computer cursor (Dekleva et al., 2021) or a robotic arm (Flesher et al., 2021; Green & Kalaska, 2011; Wolpaw et al., 2002). Additional uses of BCIs include the ability to translate neural signals to speech (Willett et al., 2023) or handwriting (Willett et al., 2021). BCIs provide great potential to aid people with very significant impairments for whom exiting assistive technologies or rehabilitation approaches are insufficient.

Intracortical BCIs have achieved a high level of performance in controlled laboratory environments (Collinger, Wodlinger, et al., 2013), enough to motivate the testing of them in real world scenarios such as in-home use (Weiss et al., 2019). However, assistive technologies are often abandoned by users due to reasons such as mismatched user needs and device function, difficulty of use, and poor performance (Phillips & Zhao, 1993). While potential BCI users desire

movement restoration and other functions, they also wish for BCIs that are reliable on a day to day basis and possess minimal setup time (Blabe et al., 2015; Collinger, Boninger, et al., 2013; Huggins et al., 2011). In long-term BCI use, natural variability in surroundings and user mental state result in highly variable BCI performance that is difficult to account for (Perge et al., 2013; Sussillo et al., 2016; Tadipatri et al., 2017). To date, one potential factor that has rarely been investigated in BCI but has been known to affect motor performance in other studies is attention (Pashler, 1994). Some evidence exists to point towards the potential of strained attention to negatively impact EEG-BCI performance (Foldes & Taylor, 2013) yet mixed results (Emami & Chau, 2018, 2020), where effects vary greatly depending on subject and session, obscure the relationship between these two features, necessitating further study before any definitive statements can be made. Furthermore, study of attention focuses primarily on EEG-BCIs, with few examining the effect on implanted BCIs.

This relationship between attention and BCI performance is the chief concern of this work. In the Background, we first begin by further describing BCIs (Section 1.1,1.2), how attention has been known to impact BCI and performance (Section 1.3), and the potential mechanism for this relationship (Section 1.4). We will then describe our recording setup (Chapter 2), and how we tested how attentional load affects BCI performance (Chapter 3) and the neural motor signal which drives that performance (Chapter 4). We will end with a discussion of the implications and impact of our findings on the future development of brain-computer interfaces (Chapter 5).

1.1 Brain-Computer Interfaces



Figure 1 University of Pittsburgh iBCI

Participant P2 using intracortical BCI to control a robotic arm (Credit: UPMC/ University of Pittsburgh Health Sciences)

A brain-computer interface (BCI) (pictured in Figure 1), is a device that measures central nervous system activity for restoration or enhancement of natural CNS outputs (Wolpaw & Winter Wolpaw, 2012). Different types of BCIs exist depending on the modality used to measure the neural signal (Nicolas-Alonso & Gomez-Gil, 2012). Two of the most common are electroencephalogram (EEG) BCIs and intracortical BCIs (iBCIs), which lie on the opposite end of the BCI spectrum (Panoulas et al., 2010). EEG BCIs use electrodes placed on the scalp to record brain activity from large areas of the brain (Abiri et al., 2019). They are the most common type of BCI due to their non-invasiveness and relatively low cost, but they have low spatial specificity that

limits the degree of control they can grant (McFarland & Wolpaw, 2017; Y. Wang et al., 2019). While spatial resolution is low, EEG does enable broad recordings from the brain, with many EEG-BCI studies extracting signals from multiple brain areas from the scalp of the brain (Emami & Chau, 2018, 2020). At the other end of the spectrum are intracortical BCIs (iBCIs), which use surgical implanted microelectrodes to record activity from single neurons, or small populations of neurons (Homer et al., 2013). Often microelectrode arrays are used to obtain recordings from ~100-200 channels resulting in a high-resolution signal which can drive a variety of devices with excellent performance (Flesher et al., 2021; Ghane-Motlagh & Sawan, 2013; Willett et al., 2021, 2023).

The difference in signal origin and quality means that each BCI modality utilizes different techniques, both in terms of subject behavior and signal processing, in order to obtain a usable signal. EEG-BCIs can use evoked potentials such as the P300 potential in response to an oddball event (Fazel-Rezai et al., 2012) or the steady state visual evoked potential in response to a flashing light (İşcan & Nikulin, 2018; Ortner et al., 2011), which can be used to select particular stimuli or commands for BCI control. For continuous control applications, EEG BCIs often detect changes in the sensorimotor rhythm (SMR), which shows a characteristic drop in power at ~10-24 Hz when a person attempts to move (McFarland & Wolpaw, 2017). Processing techniques such as common spatial pattern filters are often used to obtain clearer features from the signal (Panoulas et al., 2010). EEG-BCIs have been capable of six state control of a virtual robotic arm (Mishchenko et al., 2019), control of a quadcopter in 3d space (LaFleur et al., 2013), control of a lower body exoskeleton (Kilicarslan et al., 2013), and three dimensional cursor control (McFarland et al., 2010; Meng et al., 2018). Yet EEG-BCIs often suffer from long multi-day training times and can be fatiguing to use (Rashid et al., 2020). Furthermore, there is the question of EEG-BCI illiteracy,

where some users do not have neural features capable of driving EEG-BCIs, and how to bridge that gap (Allison & Neuper, 2010). EEG-BCIs still have much to be improved upon before their usability is satisfactory for widespread use. The setup process and calibration process alone present a significant obstacle for adoption given user preference for easy to use and set up BCIs (Blabe et al., 2015; Collinger, Boninger, et al., 2013; Huggins et al., 2011).

Inside the skull, implanted intracortical BCIs rely on neuron level information for BCI control, typically transforming estimated firing rates from small populations of neurons into control signals for external devices. During overt movements, neurons in the primary motor cortex provide descending control to the muscles in generate movement. The firing rates of these neurons are correlated to various movement parameters such as the velocity of the reach (Georgopoulos et al., 1986). Importantly, neural activity during imagined or attempted movement is very similar (Dekleva et al., 2023; Severens et al., 2015). Neural firing rates recorded from small populations of neurons during attempted movements can then be decoded into continuous control signals for reaching and grasping (Collinger, Wodlinger, et al., 2013; Flesher et al., 2021; Velliste et al., 2008) using the relationships initially identified during actual movements. While decoding approaches have become more complex, fundamentally iBCIs derive movement control signals from patterns of firing rates from small populations of neurons.

Compared to EEG recordings, iBCIs are able to access much more detailed information about movement intention, resulting in overall higher performance. While EEG-BCIs are capable of up to 3-dimensional control of something like a cursor after a great deal of training (McFarland et al., 2010), iBCIs can achieve even 10-dimensional control of a robotic arm (Wodlinger et al., 2014). The information rich signal can also allow for the decoding of handwriting to write out characters at a rate 90 per minute where an EEG based system can only do 60 characters per minute

(Willett et al., 2021). Speech prosthesis have also been created that can decode words at a rate of 62 words per minute (regular conversation is 160) (Willett et al., 2023). In both modalities, cursor control is a common application for BCI as computer access is likely to be one of the first applications of BCI and BCI control of a cursor relatively high and consistent. As such, we will use cursor control as the primary BCI task in this study. However, one disadvantage of iBCI is that single neuron recordings are unstable over time (Dickey et al., 2009; Perge et al., 2013) (See Section 1.2 for additional detail). To tackle this issue, intracortical BCIs can also make use of more stable local field potentials (LFPs) to still achieve higher performance than EEG-BCIs (A. Jackson & Hall, 2017). EEG and LFPs are similar in that they are the result of summed postsynaptic potentials but different due to the different scales at which they are obtained resulting in different levels of neuronal contribution the output signal (Cohen, 2017). Nevertheless, this similarity means analysis of EEG and LFP signal are also similar and that there are movement-related features common to both which are useful for BCI. For BCIs to achieve state of the art performance, however, traditional spike-based decoders are necessary, despite the instabilities. As such, developing ways to maintain this performance while avoiding instabilities is necessary.

1.2 Brain-Computer Interface Performance Variability

For the purposes of this thesis, we will focus on intracortical BCI performance as they enable richer and more complex control of external devices than EEG BCI. A key determinate of BCI performance is the BCI decoder, which is a set of equations that transform neural data into a real-time control signal for an external device (Dong et al., 2023). A BCI decoder is generally calibrated using neural data recorded while participants attempt to perform a task with well-defined

movement parameters (Homer et al., 2013). For example, to calibrate a BCI decoder for cursor control, the BCI user would attempt to move the cursor to targets displayed on a computer screen (Dekleva et al., 2021). The movement kinematics of the cursor would initially be controlled by the computer while the neural data associated with the attempted movements was recorded. The neural data, which is essentially a matrix of firing rates for each channel, and cursor kinematics recorded during calibration would then be used to estimate the BCI decoder that would then transform neural data reflecting movement intention into velocity commands for the computer cursor. Typically, the BCI decoder is held static after calibration is performed.

However, intracortical recordings are unstable and can change due to recording instabilities or contextual changes. In our own data, the degree to which decoders can explain kinematics can vary greatly across time due to this variability (Figure 3). Recording instabilities describe neural drift in which the actual neurons that a given electrode is recording from change (Downey et al., 2018). Contextual changes cause shifts in the neural firing properties on any given channel, such as a shift in baseline firing rate, or a change in the relationship between firing rate and a given movement parameter. Instabilities can occur both within and across days and are often significant enough to necessitate recalibration. This presents a significant barrier to the widespread use of iBCIs as recalibration is generally a lengthy process that must be performed by a trained individual (Blabe et al., 2015). Some deal with this through unsupervised recalibration that is done automatically (Degenhart et al., 2020; Wilson et al., 2023), allowing for an up to date decoder without any intervention though these demonstrations have been limited to specific participants and tasks.

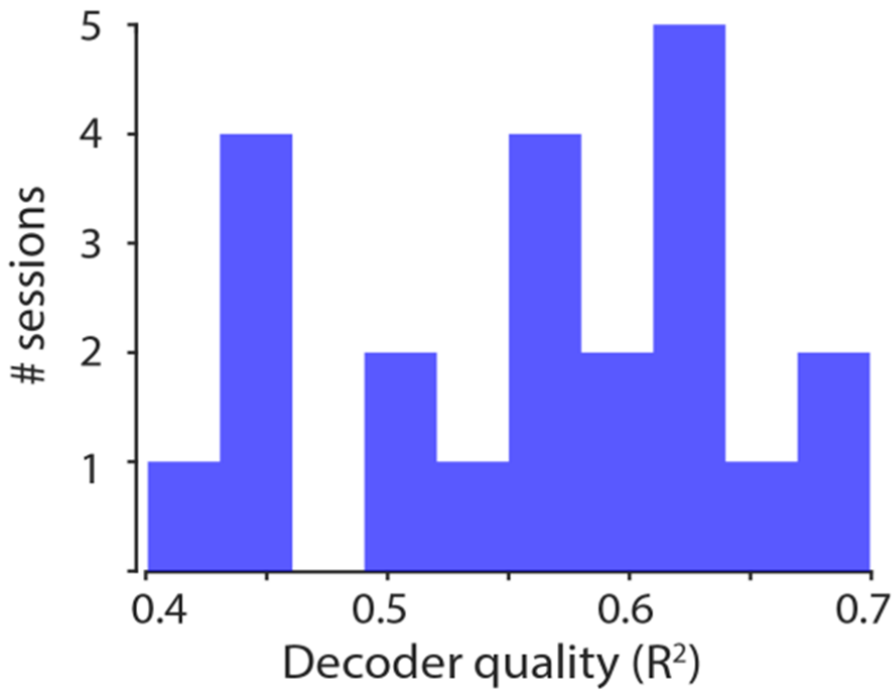


Figure 2 Decoder Quality across Time

Histogram of BCI decoder quality measured across multiple sessions, measured here as the R^2 correlation coefficient between the predicted and actual cursor kinematics

Variability due to recording instability that may occur for multiple reasons, such as micromotion of the implanted array which may result in recording from different neurons over time (Perge et al., 2013). Issues like this and other physiological mechanisms can result in significant changes in spike amplitude and firing rate within an hour of recording. This is not the case for all neuronal units, as some can be stable even across days (Downey et al., 2018) but as many as 61% of recorded units have been known to change significantly after 15 days (Dickey et al., 2009). Instabilities can manifest in other ways such as changes in spike amplitude due to micromovement of the electrode (Gold et al., 2006), which occur due to the shape of an action potential being dependent on distance to the recording device. Tissue buildup due to glial scarring from the implant may also obscure neuronal information (Szarowski et al., 2003). Similarly, neural

damage after initial implantation of the electrode array can impact signal quality as well (Suner et al., 2005) for some time after implantation.

External factors may also be responsible for changes in neural activity compared to that observed in training. For example, the act of reaching towards an object produces different neural activity than reaching without an object which must be accounted for to maintain performance (Downey et al., 2017). In terms of reaching, users also act differently when they are reaching towards something vs trying to hover over an object, with different directional information being exhibited by neurons (Sachs et al., 2015). Beyond just reaching, monkeys have been known to alter firing rate when a wider variety of motor outputs are expected to be needed (Hepp-Reymond et al., 1999). It has also been shown that the presence of rewards can alter neural activity in the primary motor cortex (Ramakrishnan et al., 2017) and that including this can improve iBCI decoding accuracy offline (Zhao et al., 2018). These papers serve to show how researchers must consider how the task context relates to training context and the decoder in order to maintain iBCI performance.

Subject state and behavior are other important variables to consider in BCI performance. For example, a measure of arousal known as neural engagement was found to influence how well non-human primate BCI users performed on a task (Hennig et al., 2021). Furthermore, different behavioral strategies can result in differences in firing rate and preferred direction as a monkey learns (Jarosiewicz et al., 2008). Beyond BCI use, neural activity also differs depending on whether someone is watching, imagining, or attempting a movement (Vargas-Irwin et al., 2018). It has also been demonstrated that using neural data from multiple days improves BCI performance due to a greater sampling of possible subject neural states (Sussillo et al., 2016). In intracortical recordings, a slow drift of neural activity has also been found to represent a signal of impulsivity

that influences decision making (Cowley et al., 2020). However, we do not currently have a good understanding of how specific changes in subject state influence neural activity, which may allow for more principled approaches to stable decoding.

One issue related to calibration is that the neural data collected during training is not necessarily reflective of that obtained during real world use. Creating calibration paradigms that better reflect actual use helps create a more accurate and consistent signal when it comes time to actually use a decoder. This has been seen with attempts to calibrate based on when a user is actually controlling a cursor (closed loop control) for example, versus merely imagining control (open loop control) (Jarosiewicz et al., 2013). Most BCI studies now include a closed-loop step of calibration in their standard procedure, however this does not account for changes that may occur outside of that calibration period, nor does it provide an understanding of what is fundamentally changing in the neural signal and what is causing that change. Better decoders and calibration paradigms can be achieved if these factors of change were understood. We suspect that many of these personal and environmental factors will impact the participant's overall attentional load, due to the added challenge of compensating for the factors, which may impact BCI performance.

1.3 Theories and Functions of Attention

There are many different forms of attention. Indeed, this presents a problem when studying or discussing attention (Hommel et al., 2019) as researchers may talk about attention, each with their own idea of what constitutes it. It is best, then, to define as specific a process as possible from the outset. The first division to make is to separate the process of top-down attention from bottom-up attention. The latter is when external stimuli draw upon attention for processing while the

former is when attention is actively and internally used to purposefully process stimuli (Katsuki & Constantinidis, 2014). From top-down attention comes the idea of executive attention, the ability to control attention in the service of task completion (Burgoyne & Engle, 2020). This is necessary for the completion of any task and in real-world scenarios, complex tasks require that we use this to accomplish multiple sub-tasks or process multiple streams of information simultaneously for purposes such as driving (Draheim et al., 2022). Yet our ability to divide our attention can be very limited.

Divided attention is often studied through dual tasking, where it can result in a drop in performance on one or both tasks and an accompanying neurological change. The addition of a secondary task essentially increases the attentional load as compared to performing the primary task alone. Many areas of the brain are involved in the maintenance of attention. Many functional neuroimaging studies have found activation in the frontal and parietal regions during attention based tasks (Coull, 1998).

Neural correlates of attention are also commonly measured with EEG. For example, a dual task driving task was shown to increase frontal area theta band frequency power and decrease parietal area alpha band frequency power (Y.-K. Wang et al., 2018). Increasing theta has also been seen in a dual task of motor and N-Back tasks (Ozdemir et al., 2016) while decreased alpha has been found during a dual task standing and verbal math experiment (Kahya et al., 2022). See Figure 5 for a picture of frontal and parietal electrodes in an EEG montage. Frontal theta power (usually found around the 4-8Hz range) is often seen as being involved in executive function and cognitive control during cognitive tasks (Cavanagh & Frank, 2014). Alpha power (generally found around the 8-12 Hz range) is thought to be involved in control of brain resources to direct these resources

to internal or external tasks (Magosso et al., 2019). As such we used these features to investigate attention in our study.

From the study of divided attention comes the idea of attention as a resource. This was first thought of as a singular resource which bottlenecked performance (Kahneman, 1973). Everyone had a certain number of resources to split between one or many tasks and using all those resources would limit performance. This initial theory assumed the same resource is used by all tasks but later on a multi-resource theory of attention emerged (Wickens, 2002). Here there are different types of resources for different tasks, such as different resources for processing visual vs auditory information. Performance issues then arise when “cross-talk” occurs, two tasks using the same pathways to obtain the same resources (Feng et al., 2014). From this concept of resources, we begin referring to the idea of attentional load. To accomplish a specific task, attentional resources are drawn upon, placing load on the attentional network. Harder or more numerous tasks may require additional resources. In the latter case of multi-tasking, performance will decrease due to cross-talk and, potentially, a lack of overall resources to cover both tasks.

Dual-tasking has been studied in several motor paradigms. For example, one study looking at the ability of older and younger adults to maintain their balance with or without an N-Back distractor, found that the presence of a 2-Back decreased performance and increased theta power (Ozdemir et al., 2016). The N-Back is a working memory task often used in dual tasking studies, where the subject must indicate matching stimuli in a sequence (Kirchner, 1958). Because of this, we used the N-Back in our study as a secondary task.

Dual-tasking can have a variety of seemingly contradictory effects on performance. In studies of driving, the presence of a secondary task may hurt, have no effect, or even improve performance (Engström et al., 2017). These mixed effects have been explained as depending on

the interactions between the primary and secondary task, with dual tasking being easiest when one of the tasks is essentially automatic in how it is performed, requiring no great thought. A similar effect may account for nonlinear attention-motor relationships in the posture control literature (Lacour et al., 2008). For example in one study investigating postural sway, it was found that performing an N-Back of increasing difficulty improved postural control as measured by increasing entropy up to a certain difficulty level, but that the most extreme N-Back levels reduced control (Haid & Federolf, 2019).

One difficulty in studying attention comes from measuring it. This partly arises on the task level, where multiple cognitive processes such as inhibition, or even multiple types of attention such as spatial attention, may be at play, creating confusion as to which process is causing what effect (Draheim et al., 2022). Furthermore, aforementioned studies have primarily focused on the effect of attention on behavioral task measures, with the assumption that attentional deficits will cause a drop in performance. Through these behavioral measures, the levels of attention and its increase or decrease can be verified indirectly. However, this effect of attention on performance is not always so clear cut as shown by the studies with nonlinear effects (Haid & Federolf, 2019; Lacour et al., 2008). Nonetheless this assumption is still often made, and if deviations exist then they are explained due to other factors such as cross-talk or limited resources, and even the concept of automaticity requires some attention be paid. As such, to best study attention it is necessary to use specific tasks are commonly used to measure a specific type of attention, such as using an N-Back in a study of divided attention (Ozdemir et al., 2016). Furthermore, using multiple proven measures of attention, both behavioral (such as accuracy) and neural (such as theta power (Y.-K. Wang et al., 2018)) can allow us to better characterize a complicated process.

1.4 Attention in Brain Computer Interfaces

The ability to focus attention is vital to everyday life but people can have trouble with task performance when presented with two simultaneous tasks, even when both are simple (Pashler, 1994). Even basic processes such as posture and gait initiation can be affected by the processing of another task (Bayot et al., 2018). As such, it stands to reason that BCI performance is likely to be impacted by attention as well, though limited studies have been completed to test this hypothesis, particularly for intracortical BCIs.

Much of the literature on attention and BCI performance comes from EEG-BCI literature. A P300-based BCI speller was found to have lower performance in high mental workload conditions as well as when the user became more fatigued (Käthner et al., 2014). Furthermore, subject state often has a complicated relationship with performance as one study found that fatigue, frustration, and attention could have either positive or negative effects on EEG-BCI performance depending on the level of the mental factor at play (Myrden & Chau, 2015). Specifically, they noted that performance was best when fatigue was moderate, as participants were motivated by the frustration to better attend to the task. In an EEG-BCI motor task, subjects were found to be sensitive to speech-related distractors which decreased their target acquisition and path efficiency (Foldes & Taylor, 2013). Another study found overall classification dropped in an EEG-BCI motor task when the subject was verbally or mentally counting from 1 to 10 repeatedly (İşcan & Nikulin, 2018). The previous two studies both tested several distractors of either varying cognitive load or varying distractor modality (speech vs listening vs thinking) but not all conditions affected performance.

Some studies have also examined the effects of distraction on the neural signal during BCI performance. One EEG-BCI based study found that distractors of various cognitive loads affected the performance of low performing participants but not higher ones (Emami & Chau, 2020). This study noted that even in participants where the performance did not change, the ratio of theta to alpha power was affected by the presence of distractions, indicating that neural signals can still change under increasing cognitive load caused by distractors. Similarly, another study found that theta power was increased by dual tasking during EEG-BCI use (İşcan & Nikulin, 2018). One study found that alpha and beta frequency power, features typically used to drive EEG BCIs (McFarland & Wolpaw, 2017), increased under visual distractors even when classification accuracy in decoding motor movements remained the same (Emami & Chau, 2018). However, these studies do not necessarily translate directly to iBCI as EEG-BCIs take more training to use and can be more fatiguing (Rashid et al., 2020).

Intracortical BCIs appear to be more robust against distractors, with only minimal performance loss during simple motor tasks (Guthrie et al., 2021), but it is difficult to make a definitive statement on this effectiveness as far less work has been done on how distractions affect iBCI use particularly for more complex and realistic tasks. One intracortical BCI study found decreased performance (in terms of time to target) during continuous speech but not shorter forms of it (Stavisky et al., 2020). This suggests that more involved distractor tasks have a greater effect on BCIs. Evidence from attentional studies in other fields such as driving also finds that the primary task matters in regards to distractor interference as well, with tasks that require active thought and effort being more affected by distractors (Engström et al., 2017).

Although studies that explore the impact of distraction on iBCI performance are rare, work in non-human primates has provided insight into the impact of various cognitive processes on

iBCI. For example, a measure of neural activity known as engagement, which has been linked to measures of arousal, has been found to both positively and negatively impact performance during learning (Hennig et al., 2021). Similarly, another study used EEG and intracortical arrays in monkeys to identify a measure of arousal neuronal activity which correlated with EEG alpha power and pupil size during an orientation change detection task (Johnston et al., 2022). In a spatial selective attention task with monkeys, EEG alpha power was found to have a nonlinear relationship with reaction time, where the best reaction time appeared at moderate alpha power, and lower or higher values of alpha power were concurrent with worse reaction time (Snyder et al., 2015). This relationship was found to be mediated by spike count correlation, which potentially explained the non-linear trend.

1.5 Goals, Aims, & Innovation

The primary innovation of this proposal comes from the combination of advanced iBCI control, whole brain neural monitoring with EEG, and the use of a dual-tasking paradigm with scalable difficulty. First, our state-of-the-art iBCI is capable of advanced control in human subjects during various paradigms (Collinger, Wodlinger, et al., 2013), including the control of a computer cursor (Dekleva et al., 2021). Working with human participants allows us to switch rapidly between conditions and has direct clinical applicability. This study extends previous iBCI work related to the impact of distractions (Guthrie et al., 2021) by utilizing a more complex task design (that includes target-guided reaching and grasping to control a virtual computer mouse vs only simple left/right translational movement). Few studies (Johnston et al., 2022; Snyder et al., 2015), and none in humans that we are aware of, have simultaneously monitored intracortical data and

EEG during BCI control. By adding whole brain EEG recordings to our iBCI setup, we were able to monitor the subject's mental state using established EEG correlates of attention, rather than relying purely on localized intracortical features. Finally, we emulated real world distractions using an dual-tasking paradigm. BCI control will be performed along with a secondary N-Back task, which has been proven to affect motor performance and neural features of attention (Ozdemir et al., 2016). Combining the advanced iBCI control with a scalable distractor allowed us to catalog the differences in outcomes when a user is faced with a mild distraction vs a more significant one. The combination of iBCI, EEG monitoring, and a task design that will induce changes in attention, will allow us to examine how attentional focus can mediate iBCI performance and motor activity. This study could set the groundwork for experiments that wish to examine how iBCIs generalize to different settings, where the subject may experience stressors, like pain or fatigue, that impact their ability to attend to BCI use.

To this end, we had two specific aims. After explaining our general methods (Chapter 2), for Aim 1 we quantified the relationship between EEG correlates of attention and iBCI performance during typical use and under two levels of attentional load (Chapter 3). We hypothesized that increased attentional load will degrade performance. Then, for Aim 2, we quantified the relationship between EEG correlates of attention with movement-related neural activity measured with both EEG and intracortical electrodes (Chapter 4). We hypothesized that increased attentional load will degrade movement-related neural activity. We then discussed how these results further understanding of iBCI performance under attentional load (Chapter 5).

2.0 Approach

2.1 Overview

In this study, two implanted iBCI participants completed a 2D+click BCI task alone or in conjunction with an N-Back of N=1 or 2 for the purposes of studying attentional load during a complex dual-tasking condition that mimics situations that may be encountered during real world BCI use. We recorded EEG and intracortical data simultaneously to access neural activity on multiple levels. We computed established measures of attention (EEG theta and alpha power), measures of the motor signal (EEG and LFP beta band power), and measures of BCI performance (success rate, completion time, path inefficiency, target acquisition rate) to examine if these measures were impacted by the dual tasking conditions compared to BCI only. We then correlated measures of attention with measures of either motor signal or performance to examine how attention impacts both neural and behavioral measures during BCI control.

2.2 Study Participants

Two participants, P2 (37 year old with C5 ASIA B SCI injury) and P4 (32 year old with C4 ASIA A SCI injury), with tetraplegia who are participating in a clinical trial of an iBCI device (NCT1894802) for restoring upper limb function completed the experiments for this project. Informed consent was obtained prior to any experimental procedures. Study participants have two intracortical microelectrode arrays (Blackrock Microsystems, Inc., Salt Lake City, UT) implanted

in the motor cortex (88 channels each for P2 and 96 for P4) and two 32 channel arrays in the somatosensory cortex. P2 was implanted approximately 8 years prior to data collection, while P4 was implanted approximately 6 months prior to data collection.

2.3 BCI Calibration

To use a BCI for cursor control, we first calibrate a decoder for use throughout the session. We begin with open-loop calibration where a user imagines movement as the cursor moves to a target in both a grasped and un-grasped state. Factor analysis, a type of dimensionality reduction, is then used to produce a 20-dimensional state space based on the neural data recorded from approximately 200 electrodes. This state space is then used to train a Kalman filter to decode 2D cursor velocity and an LDA classifier to decode click state. We repeat the process with partially assisted closed-loop calibration to train another decoder in a stepped-up manner that allows us to incorporate user response to error.

2.4 BCI and N-Back Task

Subjects performed an iBCI-controlled cursor task, which is a gamified center-out grasp and carry task (Figure 3). The participant used the BCI to move a cursor to a target that can appear in one of eight directions around, then grasp the target and carry it back to the center. This 2D+click BCI task is designed to emulate mouse use on a computer. BCI-controlled computer access is

likely to be the first application of an at-home clinical iBCI, though the findings are relevant to other BCI applications based on imagined reaching and grasping movements.

The BCI task consisted of an initial presentation phase where the target is shown, a reach phase where participants reach towards the target, a grasp phase where they grasp the target, and a center phase where they return to the center to end the trial. A black screen is then shown for two seconds to serve as an intertrial rest period. Participants had a maximum of 20 seconds to complete each non-presentation phase, where failure in any phase means failing the trial. A typical block consists of 8 trials, with 2 or 3 blocks per set. The order of the sets was randomized for each session.

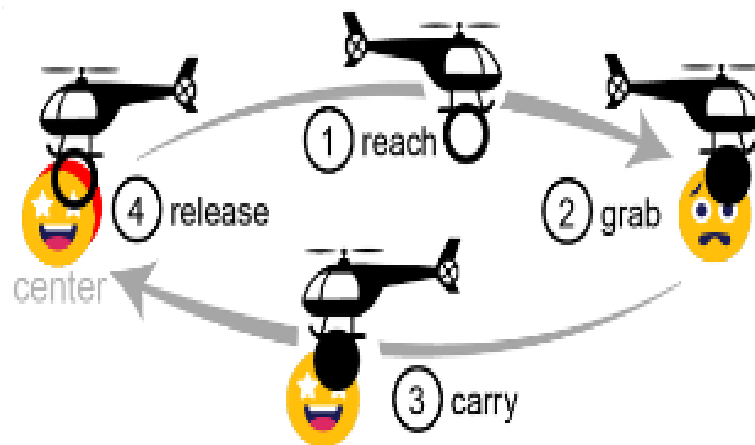


Figure 3 BCI Task

Depicts the different phases of the BCI task. Observe that the helicopter circle becomes black when grasping.

After the end of each trial, an intertrial rest period of 2 seconds is presented.

We use the N-Back as a dual task in this study. This is a task designed to test working memory (Kirchner, 1958). In the N-Back, participants were presented with letters via audio with

an inter-trial interval of 2.5 seconds while they perform the BCI test. They must verbally indicate when the letter presented matches the latter presented n (1 or 2) letters ago. The presentation of letters is be randomized. An example of 2-Back would be: I G K **G** B L, where the subject would say match on the bolded letter, G. Audio was recorded so that the subject's accuracy can be scored after the session ends. As with many dual task studies, we assume that managing this secondary task will require more attentional resources from participants due to the greater attentional load compared to only doing one task.

2.5 Session Design

We began data collection with a three-minute resting period to collect an EEG baseline. Participants were instructed to look at a fixation cross while minimizing movement during this baseline. We then calibrated the BCI decoder (as described in Section 2.3) and proceeded to the experimental conditions. EEG and intracortical neural data were recorded while the participants performed one of three conditions: 1) BCI Only, 2) BCI with mild attentional load (BCI+1-Back), and (3) BCI with moderate attentional load (2-Back test). After each condition, participants was asked to rate their mental effort on a scale as is commonly done (Paas, 1992). Here, we use a scale from 1-10. Participants were familiarized with the N-Back through practice trials before any experimental conditions were recorded. We also collected EEG and intracortical data during performance of the 1-Back and 2-Back conditions without any BCI control. The condition order was randomized each session to prevent order effects. Participants were told to focus on the cursor task as the primary task but try their best to complete the N-Back accurately. We collected 5

sessions with P2 and 6 with P4. Some sessions were cut short due to time constraints.

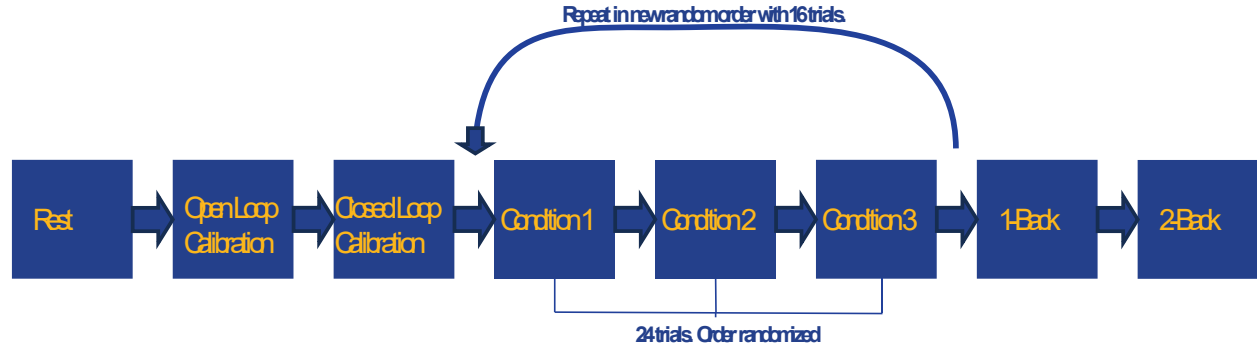


Figure 4: Session Flow

We began by collecting recording neural data during 3 minutes of rest, followed by calibration of the decoder. We then performed a block of each experimental condition in random order. Then we collected another block of each condition, randomized again but with 16 trials instead of 24. We ended each session with a block of N-Back only during which neural data were recorded.

2.6 EEG Processing

To provide a more global measurement of neural activity, EEG data was collected using 16 gtec ladybird active electrodes and gUSBamp at 256 Hz (g.tec medical engineering, Schiedlberg, Austria). The right mastoid was selected as the reference point and the ground as the left mastoid. Channel locations are shown in Figure 5. EEG data was recorded in BCI2000 (Schalk et al., 2004) and processed in EEGLAB (Delorme & Makeig, 2004). To process the data, we first filtered it with a .5-55 Hz bandpass. Bad channels were then visually identified and removed. Afterwards, we use artifact subspace reconstruction (Mullen et al., 2015) with a standard deviation of 15 to automatically identify bad data segments and remove them. We then performed a common

average reference with all remaining channels. Finally, ICA was performed to remove eye components that might contaminate the data. During resting state, this pipeline results in 5% (P2) or 18% (P4) of the data being rejected. Individual trials were further rejected if they contained any rejected data, leading to up to 5% (P2) or 48% (P4) of trials being rejected. More trials were rejected for P4 due to greater noise for reasons such as more movement and worse electrode contact. Table 1 indicates total number of EEG trials per condition per participant after rejection.

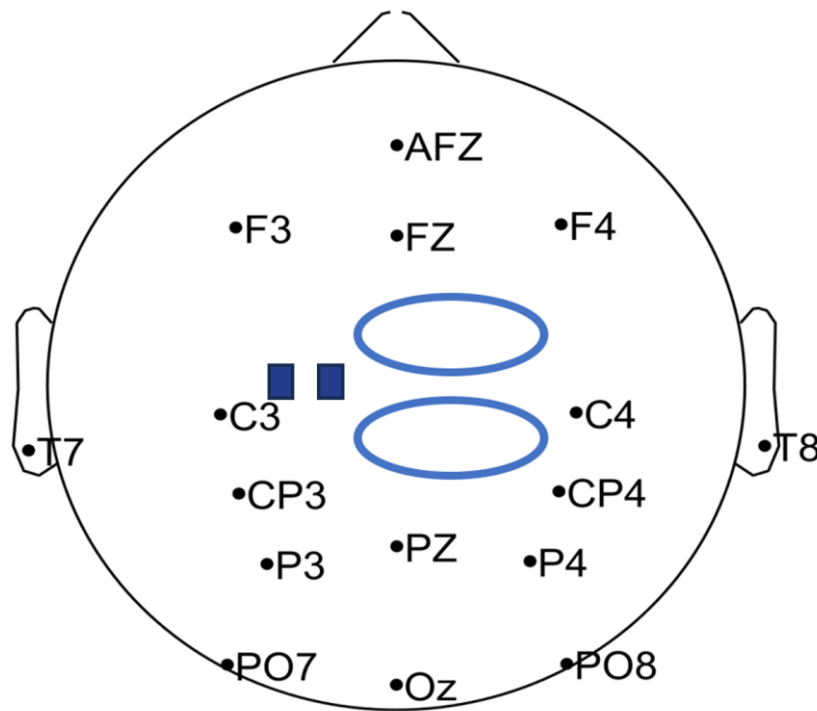


Figure 5 EEG and Intracortical Array Placement

Depicts the location and names of the 16 EEG channels. Blue ovals indicate the approximate location of head stages and blue rectangles indicate the approximate location of motor arrays on the brain. Frontal electrodes are marked by the letters F and AFZ, while the parietal-occipital electrodes are labeled with the letter P, PO, or O.

Table 1 EEG Sample Size

| Participant | BCI Only Trials | BCI+1Back Trials | BCI+2Back Trials |
|-------------|-----------------|------------------|------------------|
| P2 | 143/144 (99%) | 144/147 (97%) | 153/160 (95%) |
| P4 | 152/232 (65%) | 118/208 (56%) | 109/208 (52%) |

In Figure 6, we see trial-averaged spectrograms for the first 3.5 seconds of the reach phase, normalized to the intertrial baseline of all conditions, from the participants in the BCI Only condition. Both participants display a clear sensorimotor rhythm desynchronization, proving the feasibility of collecting EEG features during simultaneous EEG and intracortical recording.

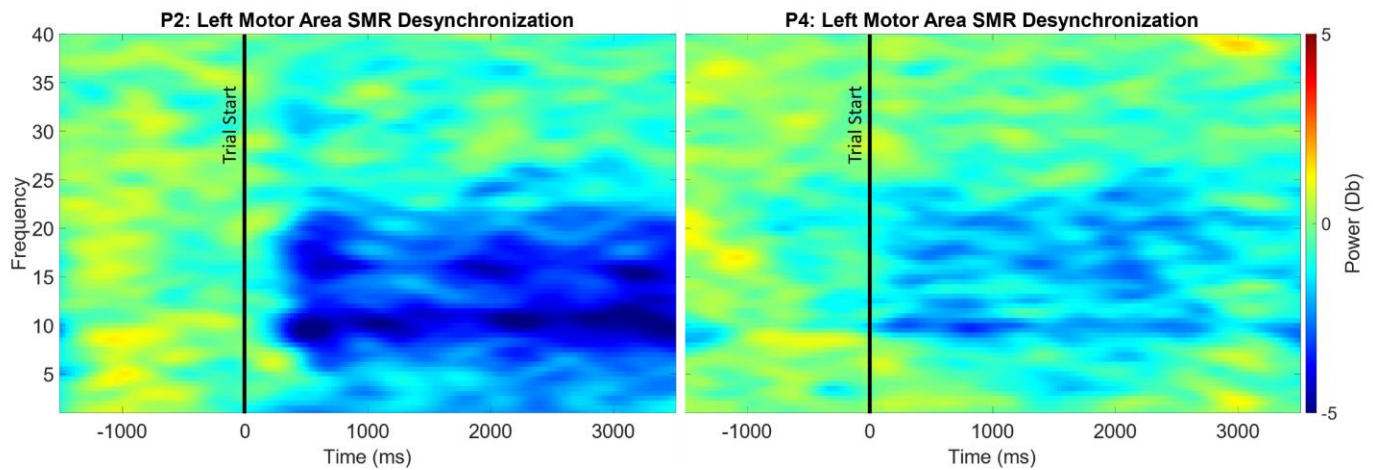


Figure 6 EEG Sensorimotor Rhythm Desynchronization

Sensorimotor rhythm desynchronization (13-30 Hz) is clearly present during cursor movement after trial start.

We extracted the attentional measures of band frequency power for theta (4-7 Hz) and alpha (8-12Hz) bands for EEG in each channel as well as the sensorimotor rhythm as represented by the beta band (13-30 Hz). To do this we first calculated the event-related spectral perturbation (ERSP) for every trial across channels for the first two seconds of reaching and calculated the

average power in a frequency band. EEG features of attention manifest across the brain but are strongest in certain regions, such as alpha primarily appearing in the parietal region and theta in the frontal (Emami & Chau, 2020). We used a region of interest approach and averaged power in the parietal-occipital (channels: Oz, PO7, PO8, P4, P3) area to obtain alpha power and frontal area (channels: AFz, Fz, F3, and F4) to obtain theta power as is common in studies of attention (Scharinger et al., 2017). We averaged over the first 2 seconds of reach to obtain a trial level measure that captures the initial period of movement towards a target before participants begin self-correcting in response to error.

2.7 Intracortical Data Processing

Intracortical signals were collected and processed using the Neuroport Signal Processor at 1000 Hz, with a 4th order 250 Hz low pass Butterworth filter applied. Threshold crossing events (-4.5 RMS) were recorded and binned (every 20 ms) to estimate spike rates. A few trials (3 for P2, 2 for P4) were rejected due to software error resulting in no intracortical data. Figure 5 displays the rough location of arrays (represented by blue rectangles) and head stages (represented by the blue ovals). From the spike rate data, we calculated the mean firing rate in each trial (consisting of the first two seconds after reach begins, as in the EEG processing) for all conditions (Wilson et al., 2023). We normalized the firing rate in the distraction conditions by the average firing rate across conditions for a trial's session. Performing this average across conditions allowed us to compare firing rates between conditions relative to a common baseline, making interpretation easier. Furthermore, it better preserves any tonic effects of condition and the higher amount of data results in a more accurate baseline.

Notch filters were implemented for the LFP for 60Hz noise and its harmonics from 60-500 Hz. From the LFP, we calculated the ERSP for every trial across the first two seconds of reach. We average this across all motor channels in the primary motor area. Then, we averaged the power within the beta band and then across time to obtain a trial level metric of the LFP beta band power.

3.0 Effects of Attentional Load on Performance

3.1 Introduction

To determine the effects of attention on iBCI performance we monitored EEG during iBCI use with and without distraction. This allowed us to test our overall hypothesis for aim 1, that increases in attentional load will be reflected in increased neural correlates of attention and degradation of iBCI performance. Specifically, we expected to see decreases in alpha band power and increases in theta band power. First, we test the sub-hypothesis that EEG correlates of attention will increase in BCI tasks performed under increasing attentional load. This is supported by prior work that shows that increased levels of attention experience during tasks such as reading, perception, and memory correlates with decreased alpha band power (Lachaux & Ossandón, 2009). Similarly, increases in cognitive load are accompanied by decreased alpha and increased theta power (Antonenko et al., 2010; Stipacek et al., 2003). Second, we test the sub-hypothesis that iBCI performance degrades under increased attentional load, something that has been observed in an EEG BCI study (Foldes & Taylor, 2013). Previous studies in iBCI have found smaller effects on performance with low-level distraction and simple BCI tasks (Guthrie et al., 2021; Stavisky et al., 2020). Finally, we test the sub-hypothesis that decreases in performance correlate with increased neural correlates of attention. Previous studies have shown that both neural markers of attention (Emami & Chau, 2020) and BCI performance (Foldes & Taylor, 2013; Stavisky et al., 2020) can be impacted by distractors, but here we test whether the amount of attentional load is correlated to degree of performance loss.

3.2 Methods

BCI task (section 2.4) performance measures include success rate (per 8 trials), reach phase completion time per successful trial, target acquisition rate (per continuous block of 16 or 24 trials), and path inefficiency for each trial of the cursor task. Path inefficiency is calculated as the ratio of the actual cursor path length to the ideal cursor path length (where a straight line to the target is equal to 1) during the reach phase of successful trials. Performance metrics, along with EEG alpha and theta power as attention metrics, were collected during BCI Only, BCI +1Back, and BCI+2Back.

Data was combined across days for statistical testing. Path inefficiency, total trial and reach trial completion times were found to have skewed distributions so they were log-normalized during statistical testing to aid normality. To control for session-to-session differences, we used a one-way ANCOVA to test the hypothesis that performance and attention metrics will differ between attentional load (i.e., n-back) conditions while controlling for the effect of session, which was included in the model as a covariate. with a separate ANCOVA per attention and performance metric. Post-hoc t-tests were used to test for differences between conditions with Bonferroni correction for multiple comparisons correction. We then used multivariate regression to test the hypothesis that measures of attention relate to measures of performance. Condition was used as a predictor to help isolate the effect of the attentional measures across conditions. The Pillai test statistic is provided for overall model significance, with individual F-tests run for predicting individual response variables. As described in section 2.6, some EEG data was rejected due to artifact contamination. Those trials were excluded from the regression analysis.

3.3 Results

iBCI performance was generally robust to attentional load challenges induced by the dual tasking N-back paradigm (Figure 7) as there were no significant differences in performance across BCI dual-tasking conditions. Neither participant showed differences in success rate (P2: $F(2,52)=.945$ $p=.395$ P4: $F(2,77)=1.605$ $p=.208$), target acquisition rate (P2: $F(2,19)=.004$, $p=.996$ P4: $F(2,28)=.165$ $p=.849$), reach phase completion time (P2: $F(2,356) =.161$ $p=.851$, P4: $F(2,631) =.549$ $p=.578$), trial path inefficiency (P2: $F(2,356) =.655$ $p=.52$, P4: $F(2,631) =.632$ $p=.532$) or total trial completion time (P2: $F(2,356) =1.101$ $p=.334$, P4: $F(2,631) =.859$ $p=.424$).

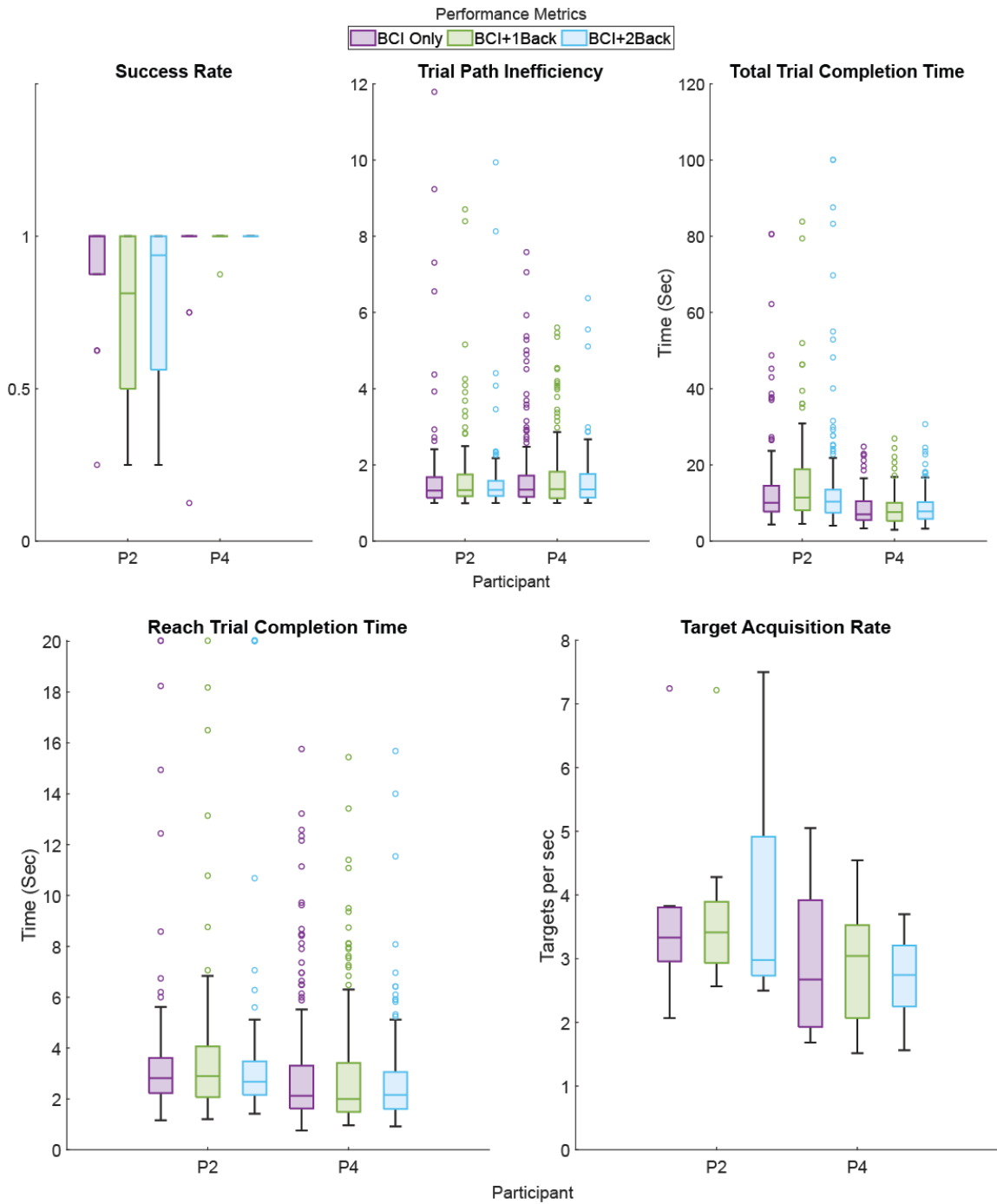


Figure 7 iBCI Performance Metrics

Performance remains stable in response to attentional load. No significant differences were observed in either participant across the three BCI dual-tasking conditions.

To confirm that participants were dividing attention between the two tasks, we show that participants were appropriately engaged in the N-Back task and not ignoring it. Figure 8 shows accuracy in identifying matches for the N-Back task, with both participants showing high scores in all conditions. When asked to subjectively rate how much mental effort a block of trials requires, participants subjectively report dual tasking as requiring more than BCI Only (Figure 9). An ANCOVA test confirms that perceived difficulty is different across conditions for both participants (P2: $F(4,23)=4.80$ $p=.006$, P4: $F(4,33)=6.75$ $p<.001$). For P2, both BCI+1Back and BCI+2Back require more effort compared to 1-Back only. For P4, BCI+2Back requires more effort than 1-Back only and BCI Only.

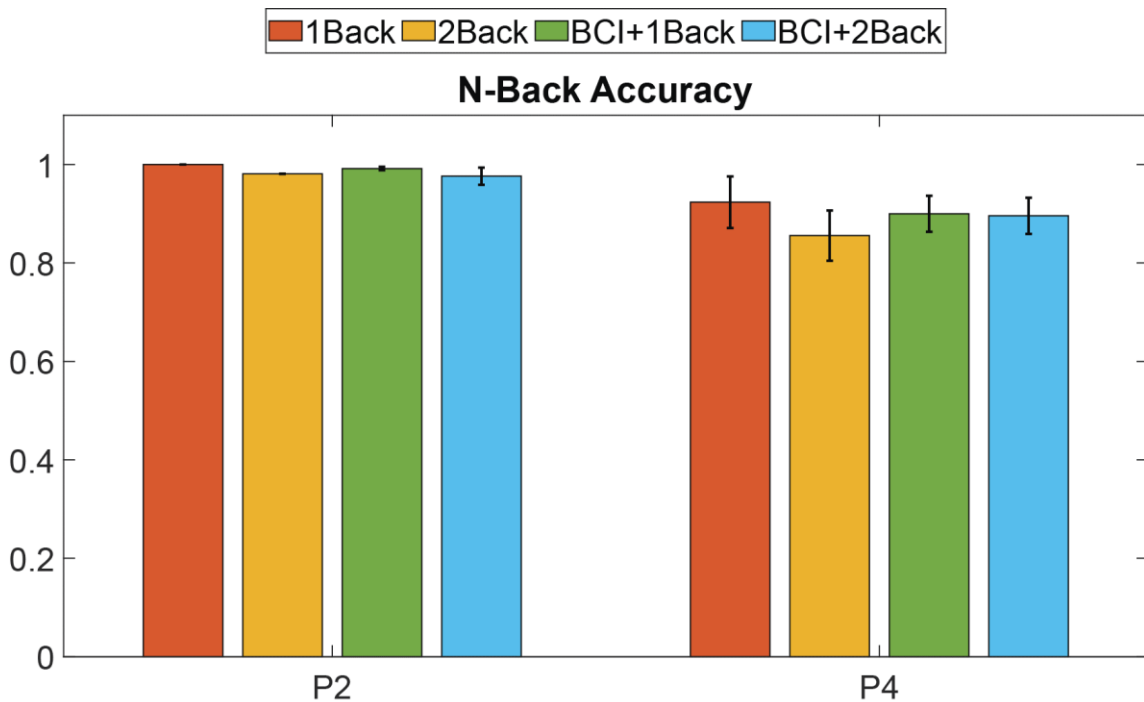


Figure 8 N-Back Accuracy

Participants were accurate when performing N-Back in all conditions. An accuracy of 1 indicates perfect performance. Any false positive or false negative is considered an error.

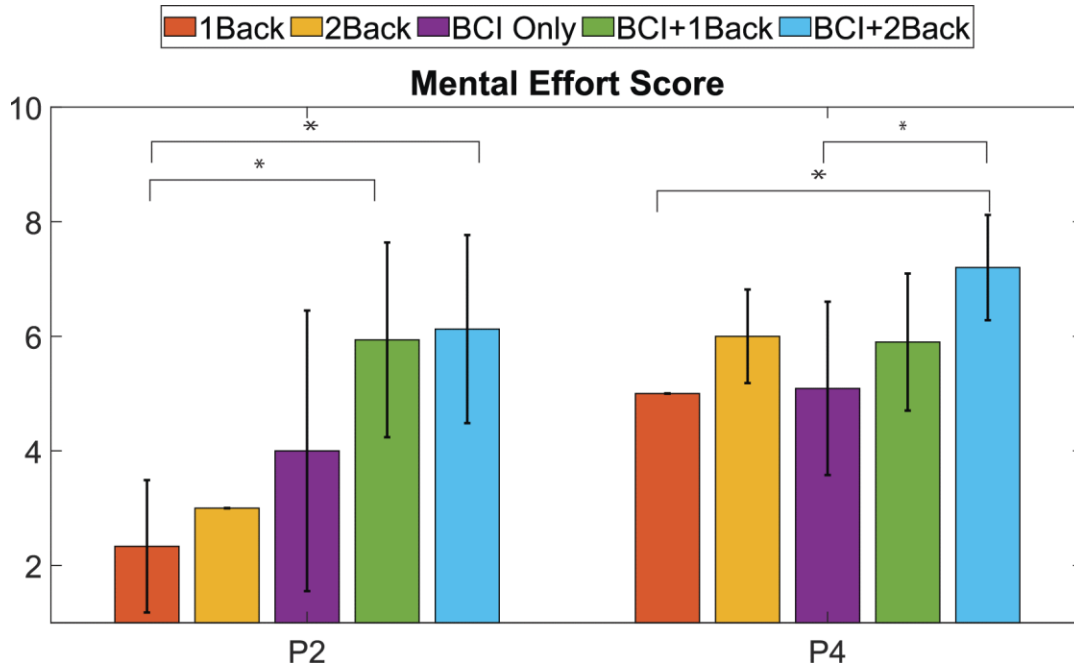


Figure 9 Mental Effort Scores

On a scale of 1-10, participants self report dual tasking conditions as requiring more mental effort than BCI Only.

When looking at neural correlates of attention (Figure 10), we see changes in frontal theta power for both participants across BCI and dual-tasking conditions (P2: $F(2,436)=5.199$ $p=.006$, P4: $F(2,375)=4.976$ $p=.007$). Specifically, for P2, it is higher in the BCI+1Back compared to BCI Only ($p<.05$) For P4, it is higher in the BCI+2Back condition ($p<.05$). Increases in frontal theta power reflect an increase in intentional load. This result is similar to what we observed when comparing theta power measured during performance of the N-Back only (without concurrent BCI performance) versus that measured at rest (Figure 11) for both participants (P2: $F(2,814)=141.32$ $p<.001$, P4: $F(2,809)=31.823$ $p<.001$), where 1-Back is higher compared to both other conditions ($p<.05$). For P2, 2-Back only is lower compared to 1-Back but still higher than rest ($p<.05$).

When looking alpha power in the parietal region during BCI and n-back dual-tasking, we found significant difference across conditions for P2 but not P4 (P2: $F(2,436)=9.039$ $p<.001$, P4: $F(2,375)=.463$ $p=.630$). For P2, BCI+1Back was higher than other conditions ($p<.05$). This result is the opposite direction expected, as we initially hypothesized there would be a decrease in response to increasing attentional load. However, this increase is also seen in both participants when looking at 1-Back only vs rest (P2: $F(2,814) =154.02$ $p<.001$, P4: $F(2,809)=18.06$ $p<.001$), where 1-Back is higher than rest ($p<.05$). P2 2-Back only is also lower than both conditions ($p<.05$). Thus, both alpha (for P2) and theta (for both participants) seem to increase and then decrease with increasing attentional load.

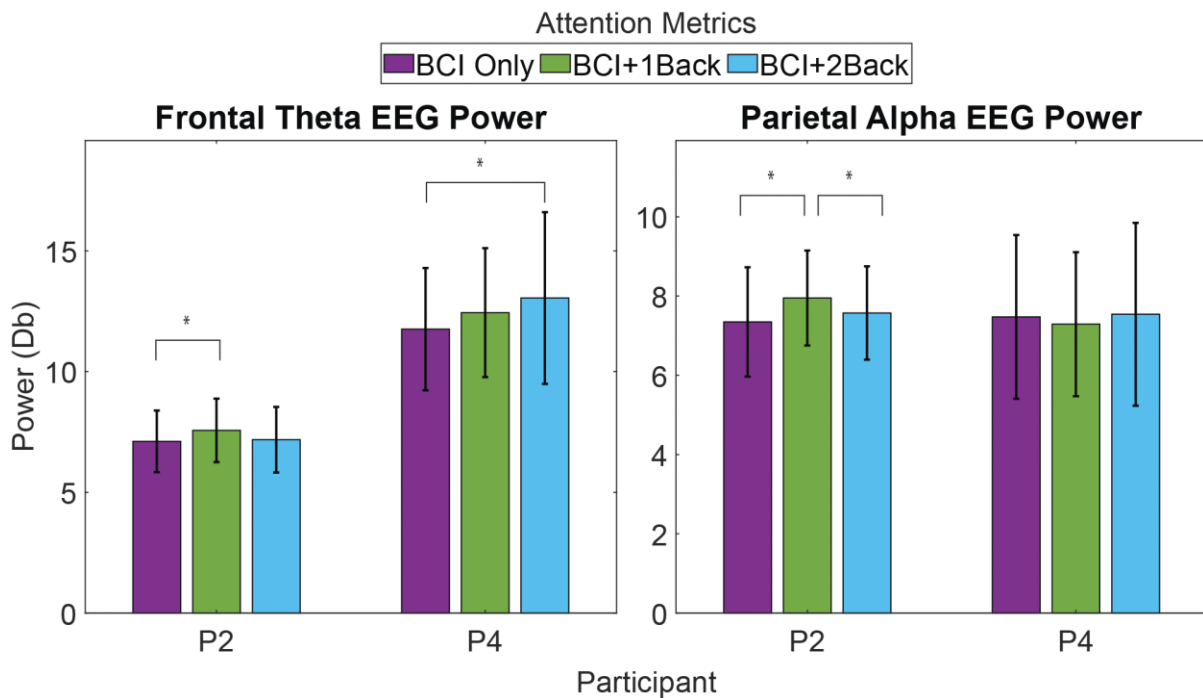


Figure 10 Attention Metrics

Participants display higher theta power in either BCI+1Back (P2) or BCI+2Back (P4) compared to BCI Only. P2 displays higher alpha power in BCI+1Back compared to BCI Only.

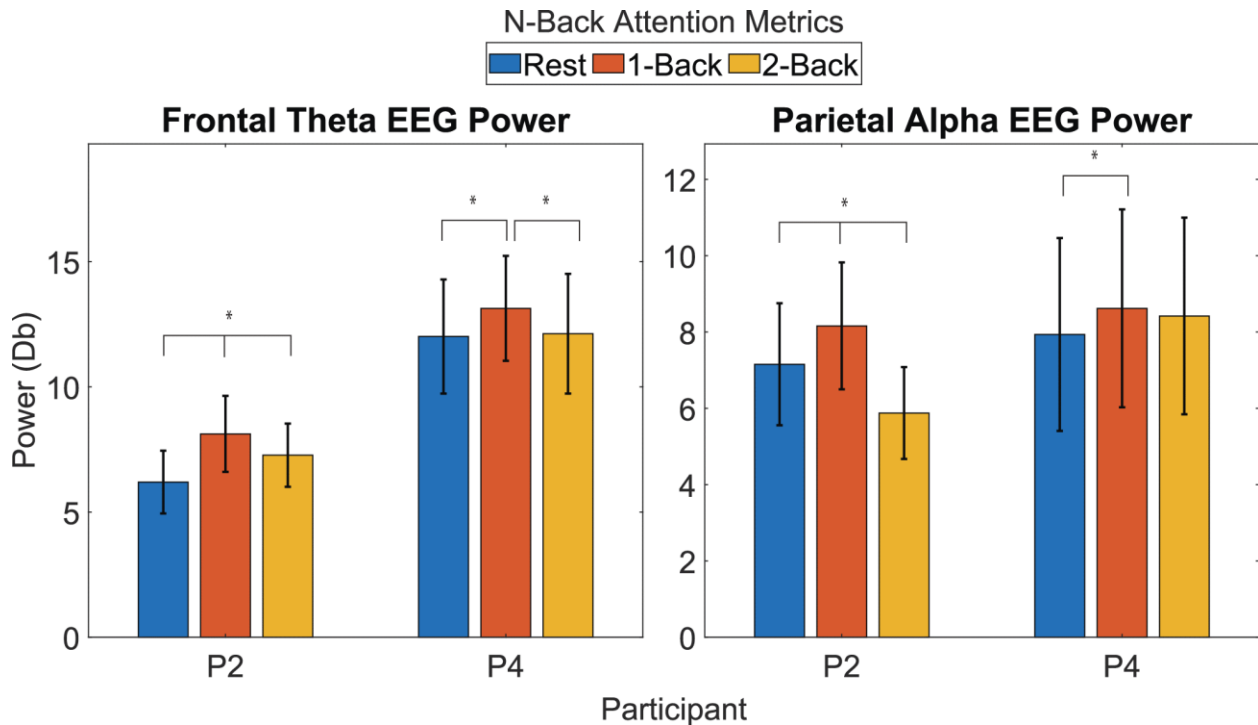


Figure 11 N-Back Only Attention Metrics

Participants display higher theta power in 1-Back compared to rest, with P2 also having higher theta power in 2-Back. Participants displays higher alpha power in 1-Back compared to rest, with P2's 2-Back alpha power being lower than other conditions.

In order to test the hypothesis that attention and performance are related, we performed regress attentional metrics with performance metrics (Figure 12) on a trial-by-trial basis. Only successful trials were included in this regression. For P2, theta power has no significant relationship with any performance predictors ($F(3,348)=0.360$ $p=.782$) but alpha power does (Table 2). P4 attentional metrics do have a significant relationship with the performance predictors, with theta and alpha power having a negative effect on all of them (Table 3), indicating that as attention increases performance improves. Both participants exhibit a significant relationship between alpha and performance predictors. In P2, alpha power has a positive effect on total trial completion time (Table 2)., whereas P4 has a negative effect on the same metric (Table 4). P2's

performance thus decreases with increasing alpha as trials take longer to complete, while P4's performance increases. Scatter plots in Figure 12 show these variables plotted against each other.

Table 2 P2 Alpha Power vs Performance Regression

Results of multivariate regression. Significant effects are highlighted in gray. Alpha is found to predict total time.

| P2: [performance] = condition + alpha_eeg | | | | | | |
|---|--------|----------|---------|---------|------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall alpha_eeg Effect | 3 | 348 | 4.690 | .003 | N/A | N/A |
| Path_inefficiency | 3 | 350 | .6169 | .366 | .007 | .002 |
| Total_time | 3 | 350 | 4.736 | .005 | .04 | .03 |
| Reach_time | 3 | 350 | .446 | .288 | .011 | .003 |

Table 3 P4 Theta Power vs Performance Regression

Results of multivariate regression. Significant effects are highlighted in gray. Theta is found to predict all metrics of performance.

| P4: [performance] = condition + theta_eeg | | | | | | |
|---|--------|----------|---------|---------|-------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall theta_eeg Effect | 3 | 366 | 4.6622 | .003 | N/A | N/A |
| Path_inefficiency | 3 | 368 | 4.076 | .003 | -.009 | .02 |
| Total_time | 3 | 368 | 3.676 | .001 | -.011 | .03 |
| Reach_time | 3 | 368 | 3.812 | .011 | -.011 | .02 |

Table 4 P4 Alpha Power vs Performance Regression

Results of multivariate regression. Significant effects are highlighted in gray. Alpha is found to predict total time.

| P4: [performance] = condition + alpha_eeg | | | | | | |
|---|--------|----------|---------|---------|-------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall alpha_eeg Effect | 3 | 366 | 3.303 | .020 | N/A | N/A |
| Path_inefficiency | 3 | 368 | 1.295 | .479 | -.003 | .001 |
| Total_time | 3 | 368 | 2.731 | .005 | -.013 | .02 |
| Reach_time | 3 | 368 | 2.392 | .132 | -.010 | .006 |

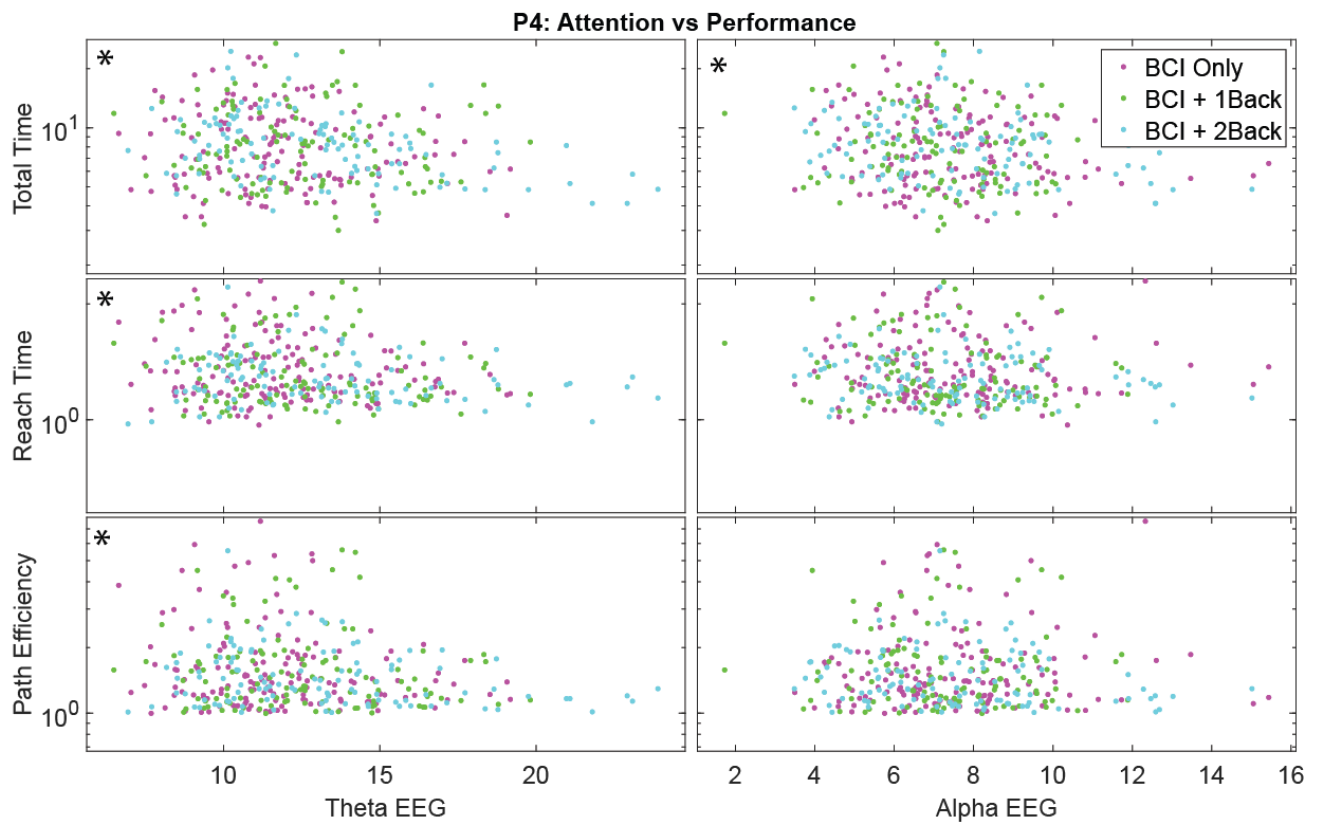
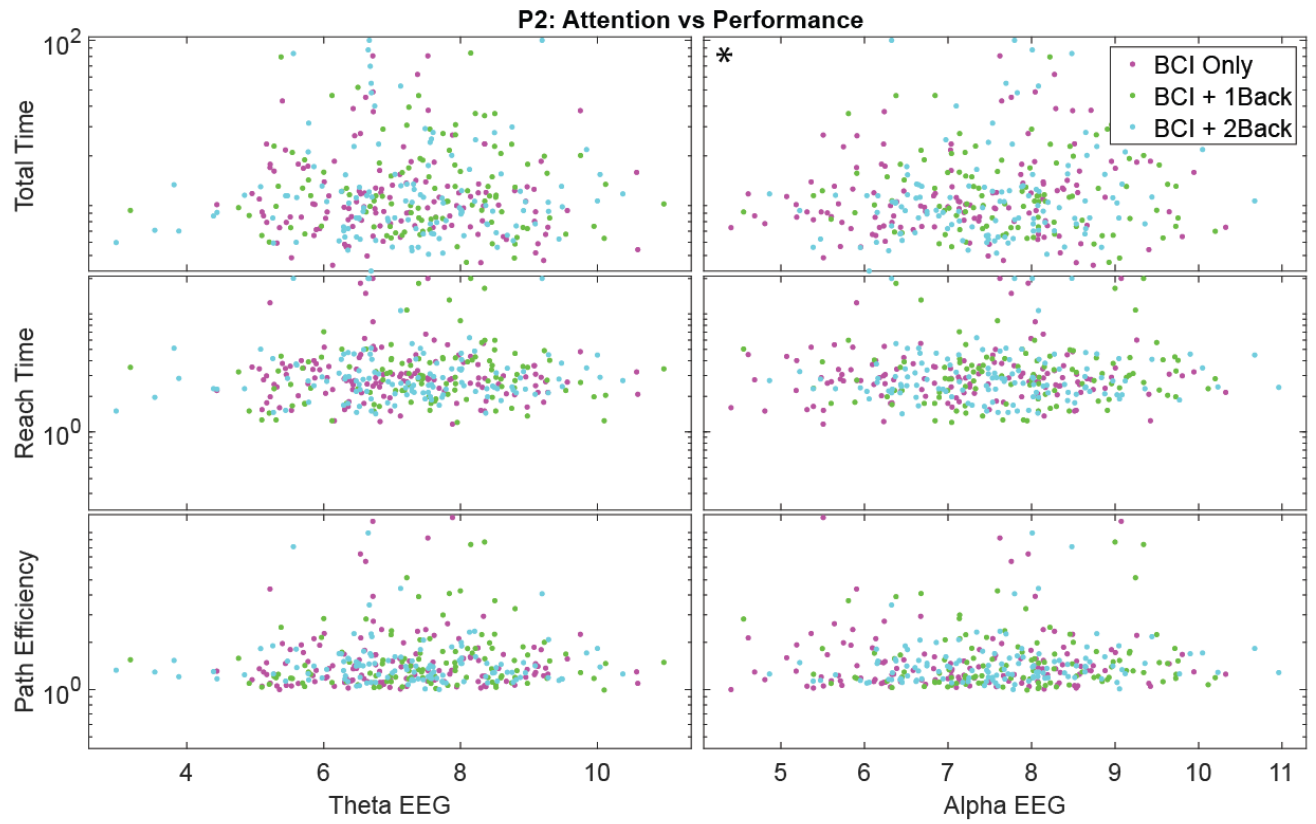


Figure 12 Attention & Performance Scatter Plots

Scatter plots of attention and performance variables. Performance values on the y-axis are shown on a log axis.

Asterisks indicates that the two variables were significantly related when modeled using regression.

3.4 Discussion

3.4.1 Attention Change as Attentional Load Increases

In this study, we observed a complex relationship between EEG theta power and attentional load. In previous dual tasking studies, theta power has been found to increase compared to single asking (Ozdemir et al., 2016). Although we also saw this effect, it was not consistent across conditions. P4 displayed an increase only in BCI+2Back, the highest load condition. This could imply that BCI+1Back was simply not complex enough to induce altered theta despite the subject reporting it required more mental effort than BCI Only. This would not explain why P2 demonstrated increased theta in the BCI+1Back condition but not BCI+2Back. In the case of P2, 2-Back theta power is higher than rest but also lower than 1-Back, whereas P4 2-Back is not significantly different from rest.

Alpha power exhibits a similar trend in P2 for both dual tasking and single tasking. However, this goes against our initial hypothesis of alpha decreasing during attentional load. In both metrics, this non-linear trend in theta seems to be an effect that occurs when progressing from 1-Back to 2-Back regardless of whether a BCI task is added to the cognitive task or not.

Alpha and theta band EEG power follow an inverted U-shaped trend in P2. Similar trends in neural metrics of cognitive load have been seen in single-tasking contexts. One study measuring

prefrontal cortex activation in fMRI during an N-Back, ranging from N=1 to N=6, found that activation was highest at N=3 but then proceeded to decline (Lamichhane et al., 2020). One interpretation for this is that this reflects a shift in processing strategy where the brain regions which are active shift to handle the increasing load.

3.4.2 Why Does Alpha Power Increase

In the literature, alpha power is generally found to decrease during dual tasking and attentional tasks (Kahya et al., 2022). We expected this to occur in this study but instead it increased. This is not wholly unknown in the literature, however. A previous study of mental workload during operation of a P300 EEG-BCI found increased alpha during dual tasking (Käthner et al., 2014). As in ours, their secondary cognitive tasks were displayed through audio, and they noted that auditory stimulation has been found to increase alpha activity. They also discuss the alpha inhibition theory (Klimesch et al., 2007), which states alpha increases to inhibit non-essential brain regions to maintain task performance. A similar result and theory was exhibited by a study which looked at the N-Back in young and old adults, and found that older adults exhibited an increase in alpha power with increasing N-Back load whereas young adults did not (Käthner et al., 2014). (İşcan & Nikulin, 2018), also find that alpha power was negatively correlated with performance when BCI users had to listen to verbal counting, attributing the effect to attempts by participants to inhibit the distraction sounds. Overall, it is possible that the increased alpha in 1-Back is due to participants attempting inhibition so as to better handle increasing attentional load. However, this alone would not explain why a similar increase is not seen in the 2-Back single and

dual task conditions but that may be explained by prior theories on the non-linear nature of neural activity as a measure for load.

It is also interesting to note that increased alpha power may be indicative of mind-wandering (Compton et al., 2019). If this is the case in our participants, it would fit with the theory that poor performance in the BCI+1Back is due to a lack of engagement relative to other conditions. The fact that alpha activity during rest is lower than 1-Back may seem to go against this, but participants were told to keep a clear mind and focus on a fixation cross during rest, partly to prevent mind wandering in the first place.

The fact that alpha power is also increased in 1-Back only (without concurrent BCI performance) compared to rest and 2-Back only also indicates that in these participants, in this study, increased alpha does reflect a response to increased attentional load in a similar manner as theta power does. Much like theta power though, this response is load specific.

3.4.3 Performance is Robust to Attentional Load

Participants exhibited no changes in performance across the different conditions as we initially expected. While such robustness is now unknown in the literature, the level of attentional load at play here makes this nonetheless surprising. It appears then, that iBCI control is highly robust and capable of managing high levels of attentional load. This is more striking when comparing iBCI to EEG-BCI. Studies of the latter technology have found comparatively greater effects of attention. In one study, there was a large effect ($\eta_p^2 = .31$) that led to a 20% drop in BCI performance during a triple task of 1D BCI control, maintaining cruise altitude on a flight simulator, and performing attentional tasks (Vecchiato et al., 2016). In another study, EEG-BCI

performance drops, in a BCI+speech task, ranged from 5% to 10% depending on the classifier used (İşcan & Nikulin, 2018). These results indicate that iBCI may be more robust against distractors than EEG-BCI. As such, the study of attentional load may be of greater importance to EEG-BCI researchers than those working with iBCI.

3.4.4 Attention-Performance Relationships

In the previous sections of this discussion, we looked at condition average metrics to examine total effects. However, attention fluctuations may manifest on a smaller time scale, where its effects were more subtle. To detect this, we performed multivariate regression between measures of attention and measures of performance. We found that P4 appeared to exhibit increases in performance with increases in attention, while P2's performance decreased.

Specifically, increases in alpha for P2 resulted in increases in total trial completion time, showing that higher attention is related to worse performance. This is similar to the negative correlation found between BCI performance in alpha power when a listening task is presented for dual tasking (İşcan & Nikulin, 2018). However, P4 shows improvements in performance with increasing alpha. The different participant performance baseline may explain this divergence. P2 has been implanted long-term and his implant has deteriorated to the point where poor signal quality impacts performance. P4 was more recently implemented and has higher, more stable performance overall. As a result, P2 may be more vulnerable to load than P4 is. This is also supported by the finding that low performing BCI users, but not high performers, possess a moderate correlation with subjective mental effort scores given by the NASA-TLX during a

BCI+distraction dual task (Emami & Chau, 2020). Furthermore, the fact that P4 is not only not affected by distraction, but even improves slightly because of it could be due to a cognitive load theory which states that people perform better under mild load (S. A. Jackson et al., 2014; Vallès-Català et al., 2021). This improvement may occur due to avoid complacency or forcing greater focus from the participant.

4.0 Effects of Attentional Load on the Motor Signal

4.1 Introduction

To determine the effect of attentional load on the motor signal we quantified changes in movement-related activity measured with EEG and intracortical recordings while attention was challenged with the N-Back task. From this we tested the overall aim 2 hypothesis that movement-related activity, which drives BCIs, is degraded by increases in attentional load. We first tested the sub-hypothesis that the neural motor signal degrades as the distraction level is increased. The sensorimotor rhythm desynchronization generally manifests in a decrease in beta band power compared to rest during movement (McFarland & Wolpaw, 2017). Previous work has shown that under the effect of distractors, this desynchronization during movement is reduced, signifying a disruption of the rhythm (Emami & Chau, 2018). We measured this desynchronization in the EEG and more locally in the intracortical LFPs. We also measured mean firing rate, which has been related to performance in iBCI tasks (Wilson et al., 2023) We then tested the sub-hypothesis that decreases in the movement-related activity are related to increases in EEG measures of attention. These analyses will aid in examining aim 2's overall hypothesis that the motor signal is weakened with increased attentional demands and this change correlates with increases in measures of attention.

4.2 Methods

As in Aim 1, we utilized a one-way ANCOVA with session as a covariate to test the hypothesis that attentional load during a BCI+NBack dual task (section 2.4) affected measures of the motor signal (section 2.6, 2.7). Multivariate regression was used to test for relationships between measures of attention (theta and alpha power) and the motor signal (firing rate, EEG beta power, and LFP beta power).

4.3 Results

We analyzed three metrics of the motor signal for both participants to examine whether or not attentional load impacts the neural signal that drives BCI (Figure 13). Neither participant shows differences in the EEG beta band power (P2: $F(2,436)=1.010$ $p=.300$, P4: $F(2,375)=2.604$ $p=.075$) or the intracortical LFP beta band power (P2: $F(2,444)=1.743$ $p=.176$, P4: $F(2,642)=1.584$ $p=.206$). We examined raw beta band power so an increase in power would have signified less beta band synchronization and therefore less movement-related modulation. P4, but not P2, shows difference in intracortical firing rate (P2: $F(2,444)=.397$ $p=.672$, P4: $F(2,642)=3.291$ $p=.038$). Specifically, his firing rate is higher in the BCI+2Back condition, compared to BCI Only ($p<.05$), signifying a stronger motor signal compared to BCI Only. Generally, a higher firing rate would be considered to indicate greater movement-related modulation.

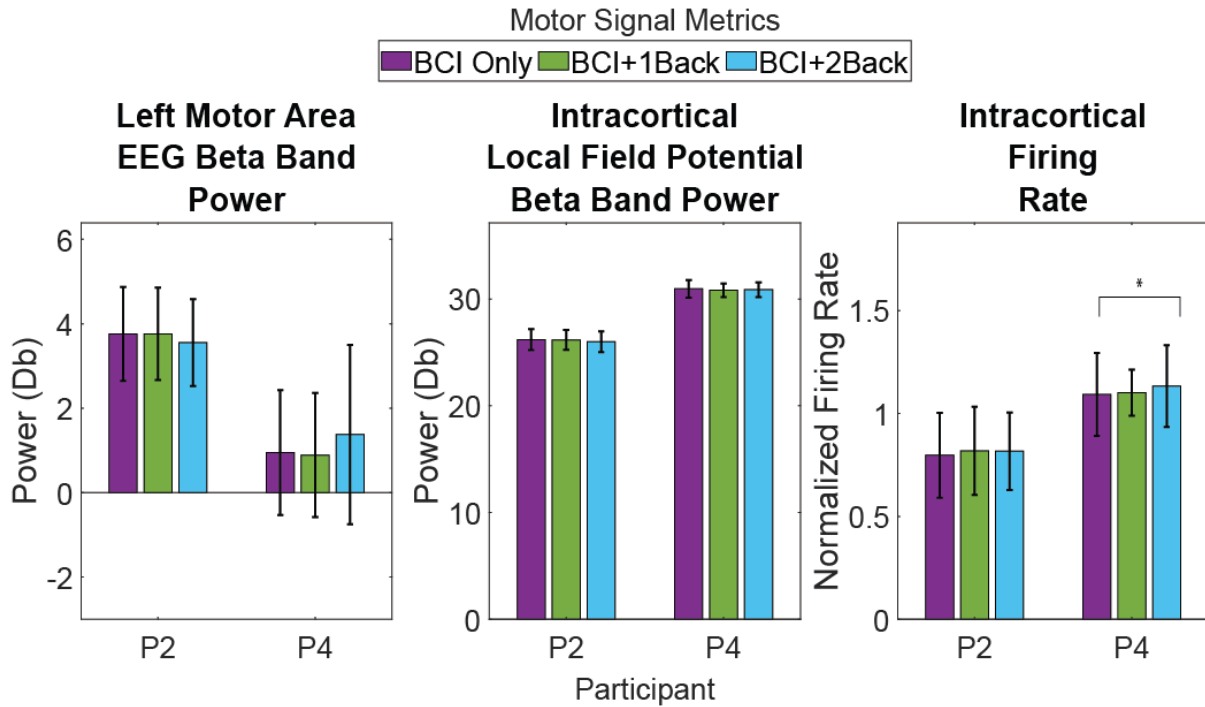


Figure 13 Motor Signal Metrics

Figure depicts three measures of the motor signal from the EEG and intracortical data. P2 exhibits no differences. P4 exhibits an increase in intracortical firing rate in BCI+2Back compared to BCI Only, signifying an increase in the motor signal.

We then performed multivariate regression to identify relationships between attention metrics and the motor signal on a trial-by-trial basis (Figure 14). Theta and alpha power were significantly related to motor signal metrics for both participants. In P2, theta power had a positive relationship with beta EEG power and beta LFP power and a negative relationship for firing rate (Table 5). This indicates that increasing attention correlates with a degrading motor signal. Alpha power had similar relationships with the motor signal metrics for P2 (Table 6). In P4, theta had a positive effect on beta EEG power but a negative effect on beta LFP (Table 7). Thus, attention correlates with a worse motor signal in beta EEG band power but not in beta LFP. In P4, alpha

power had a positive effect on beta EEG power and beta LFP power, indicating a worse motor signal with increasing alpha power (Table 8).

Table 5 P2 Theta Power vs Motor Signal Regression

Results of multivariate regression. Significant effects are highlighted in gray. Theta is found to predict measures of the motor signal.

| P2: [motor_signal] ~ Condition + theta_eeg | | | | | | |
|--|--------|----------|---------|---------|-------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall theta_eeg Effect | 3 | 434 | 23.0428 | <.001 | N/A | N/A |
| Beta_eeg | 3 | 436 | 19.64 | <.001 | .272 | .11 |
| Beta_lfp | 3 | 436 | 12.55 | <.001 | .197 | .07 |
| Firing_rate | 3 | 436 | .582 | .817 | -.002 | <.001 |

Table 6 P2 Alpha Power vs Motor Signal Regression

Results of multivariate regression. Significant effects are highlighted in gray. Alpha is found to predict measures of the motor signal.

| P2: [motor_signal] ~ Condition + alpha_eeg | | | | | | |
|--|--------|----------|---------|---------|------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall alpha_eeg Effect | 3 | 434 | 46.780 | <.001 | N/A | N/A |
| Beta_eeg | 3 | 436 | 26.87 | <.001 | .331 | .15 |
| Beta_lfp | 3 | 436 | 18.24 | <.001 | .249 | .11 |

| | | | | | | |
|-------------|---|-----|-------|-------|-------|-----|
| Firing_rate | 3 | 436 | 17.56 | <.001 | -.052 | .10 |
|-------------|---|-----|-------|-------|-------|-----|

Table 7 P4 Theta Power vs Motor Signal Regression

Results of multivariate regression. Significant effects are highlighted in gray. Theta is found to predict beta EEG power and beta LFP power.

| P4: [motor_signal] ~ Condition + theta_eeg | | | | | | |
|--|--------|----------|---------|---------|-------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall theta_eeg Effect | 3 | 373 | 70.562 | <.001 | N/A | N/A |
| Beta_eeg | 3 | 375 | 73.31 | <.001 | .349 | .36 |
| Beta_lfp | 3 | 375 | 4.17 | .030 | -.029 | .01 |
| Firing_rate | 3 | 375 | 7.472 | .139 | .004 | .006 |

Table 8 P4 Alpha Power vs Motor Signal Regression

Results of multivariate regression. Significant effects are highlighted in gray. Alpha is found to predict beta EEG power and beta LFP power.

| P4: [motor_signal] ~ Condition + alpha_eeg | | | | | | |
|--|--------|----------|---------|---------|------|------------|
| Variable | Num Df | Denom Df | F Value | P Value | Coef | η_p^2 |
| Overall alpha_eeg Effect | 3 | 373 | 79.026 | <.001 | N/A | N/A |
| Beta_eeg | 3 | 375 | 70.87 | <.001 | .484 | .35 |
| Beta_lfp | 3 | 375 | 4.397 | .021 | .043 | .01 |

| | | | | | | |
|-------------|---|-----|-------|------|------|------|
| Firing_rate | 3 | 375 | 6.943 | .405 | .004 | .002 |
|-------------|---|-----|-------|------|------|------|

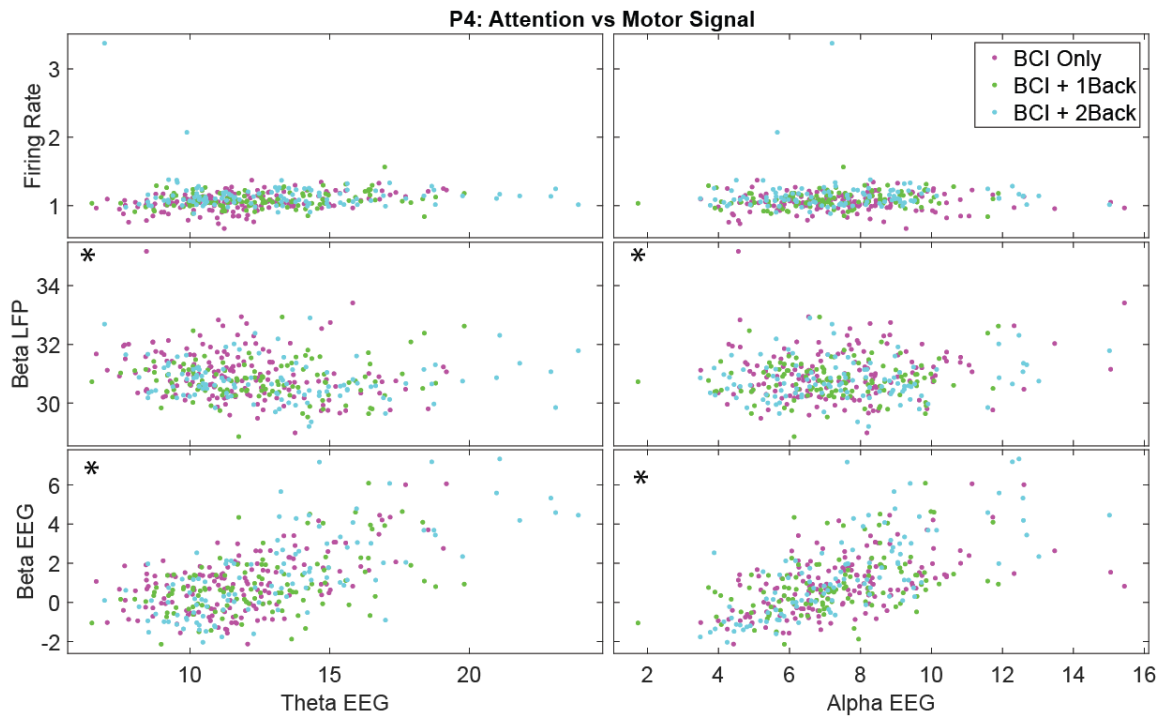
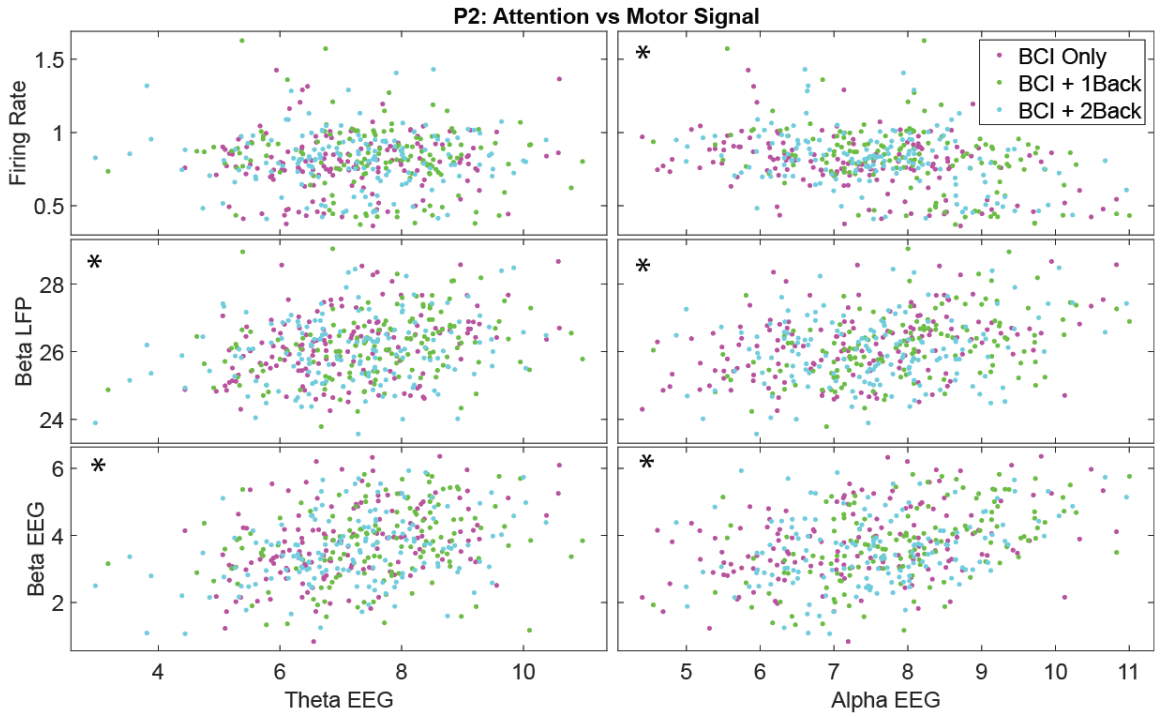


Figure 14 Attention & Motor Signal Scatter Plots

Scatter plots of attention and performance variables. Asterisks indicated that the two variables were significantly related when modeled using regression.

4.4 Discussion

4.4.1 Movement-Related Activity Remained Stable under Attentional Load

We initially hypothesized the changes in performance and the motor signal would occur in response to increased attentional load, with the latter providing a potential mechanism for why attentional load impacts performance. However, performance was stable overall. Similarly, we see that there is no deterioration of performance in either participant. Across participants, there was no degradation in the motor signal across conditions. This could indicate that their BCI control were good enough that they did not need to alter their motor signal to compensate for the attentional load. This is contrary to a previous EEG-BCI study that showed typical motor features, such as the EEG beta power desynchronization, to be disrupted to during dual tasking (Emami & Chau, 2018). It is also known that in non-BCI motor tasks, dual tasking also disrupts beta power. For example, high beta power is known to occur when young, old, and participants with Parkinson's walk while performing an auditory cognitive task (Possti et al., 2021).

In the BCI+2Back condition for P4, we in-fact see a small increase in the intracortical firing rate. This increase indicates an improvement in modulation for the neuronal population and indicates a stronger motor signal. This unexpected increase may be reflective of the lack of performance drop in BCI+2Back. Because the participant is able to increase his motor signal,

whether due to increased engagement or some other reason, he is able to maintain his performance in a way that he cannot in BCI+1Back.

4.4.2 Attention Metrics Exhibit Complex Relationships with Individual Motor Signal

Metrics

We performed multivariate regression to identify the effects of attentional metrics on the motor signal on a small-scale trial-by-trial level. Effects were similar across participants with one exception. In P2, increases of attentional metrics were related to degradations of the motor signal, as expected. The fact that this occurs here but not when comparing conditions could indicate that these motor signal metrics are more suited to trial level discrimination rather than across conditions. Attentional changes were also related to changes in the motor signal in P4 as well, but the effects are more mixed. Increases in theta predict increases in beta EEG power, as expected, but also predict decreases in the beta LFP power. Alpha EEG power, by contrast, predicts increases to both LFP and EEG beta power. The different predictive powers of alpha and theta may be explained by differing processes, with theta being primarily involved in executive functions (Cavanagh & Frank, 2014) and alpha being related to inhibition of non-task related processes (Klimesch et al., 2007). Theta's differing effects on the different metrics could indicate that a complex set of mechanisms is at play for the purposes of maintaining overall performance.

The strongest and most consistent effect observed was that as theta and alpha power increased, so did EEG beta power. Given that all are metrics originating from EEG, it may be natural for them to have a greater relationship than theta/alpha would have with intracortical metrics. But EEG theta/alpha and beta are not always related in such a way. For example, one well

known marker of cognitive processing load is the theta/beta ratio (Clarke et al., 2019), which correlates with increasing cognitive load. However, this ratio usually comes about due to theta increasing and beta decreasing (Lubar, 1991) whereas in this study we see that increases in theta was predictive of increases in beta. One study looked at theta-alpha-beta correlations in the frontal region of the brain and found that it was higher in individuals with higher executive function skills (Basharpoor et al., 2021). Without further experiments, it is difficult to say that this is the factor at play in this study.

5.0 Summary and Conclusions

In this study we investigated the effects of attentional load on intracortical BCI performance and the motor signal which drives it. We characterized attention using objective EEG measures of attention and employed multivariate to understand how they can help predict performance and the motor signal. First, we showed that performance was stable across conditions. Then we showed that attention can be measured by using EEG measures. We also showed that there were limited effects on the motor signal, with the only change being an increase in strength as measured high intracortical firing rate in BCI+2Back for one participant. Finally, we showed that attentional metrics can predict performance and motor signal metrics on a trial-by-trial level. We discussed how these features manifested in subject and condition specific ways and how their relationships to each other may be complex and mediated by a variety of cognitive processes.

5.1 Impact

This work adds to the small literature of attention in BCI by demonstrating how attention can relate to performance and the motor signal under differing levels of attentional load. It is one of very few studies that look at the impact of attention or distraction during iBCI control (Guthrie et al., 2021; Stavisky et al., 2020). Unlike these previous studies, attention was quantified with whole brain EEG measures. We show that this is possible in humans without significant artifacts and enabling simultaneous investigation of local, intracortical movement-related activity and more complex cognitive processes that involve the entire brain. This lays the groundwork for future

research that wishes to perform multi-modal studies involving both intracortical recordings and EEG to take advantages of both modalities' advantages.

Furthermore, this study quantified the effects of attention at multiple levels of a difficult cognitive task in addition to an already difficult iBCI task. This allowed us to observe effects that occur under a wide range of attentional load. By doing so, we can better speak to how iBCI may be affected by more real-world conditions where users may experience an array of distractions. Finally, it allows us to demonstrate how iBCI can remain high even in the face of substantial attentional load.

5.2 Limitations and Future Work

The primary limitation of this work was the low sample size. Due to the invasiveness and cost of iBCI, studies involving the technology are generally limited in how many participants can be involved in any given experiment. This is especially an issue for psychological or cognitive research, where low effect sizes and high variability necessitate a high sample size (Funder & Ozer, 2019). Indeed, from this and other BCI studies, it is clear that whatever effects of attention exist are best moderate in size. While iBCIs are gaining in popularity and are commercializing, it may still be some time before large sample sizes can be possible. In the meantime, longer longitudinal studies may help alleviate this by allowing us to study the stability of attentional effects.

The second limitation of this work is that we rely on a-priori features of attention. While these features are well studied in the literature, they are not necessarily correct for every individual.

It is conceivable that there may be other features that better track the changes in attention that occur due to attentional load and even that these features would differ per individual. Recent studies have looked at data driven methods such as by using feature selection and machine learning models to decode attentional load (Xu et al., 2023). Future studies that look at attention in iBCI may wish to the same, perhaps also leveraging the information rich signal of intracortical arrays to quantify attention without the use of EEG.

We limited ourselves to the N-Back at two levels for this study. The N-Back was chosen such to be difficult enough to cause load but not so difficult so as to destroy performance in both tasks. This is partly because this is a usability study that is meant to reflect real-world conditions and a user can only be expected to withstand so much attentional load. However, further increasing the difficulty of the N-Back to higher levels, to the point where maintaining iBCI performance becomes untenable, may allow us to gain information on how attention behaves at this breaking point which could inform how we study how attention at lower levels of load as well. For example, there may be effects that are unclear until we observe them at this high level of load. Furthermore, the N-Back is a working memory task and may not have the same effects on performance as other types of tasks. Using different types of secondary tasks may reveal trends in BCI performance that are dependent on the type of secondary task being performed.

This study helps lay the groundwork for a complex study of the cognitive process which drives BCI performance and mediates the neural signal. Attention is likely but one of the many processes involved and future work will have to take care to disentangle the effects of attention from other processes to be able to fully understand BCI control. Such studies are needed to help make BCIs even more robust and easy to use.

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