Evaluating Person-Centered Factors Associated with Brain-Computer Interface Access to a Commercial Augmentative and Alternative Communication Device

By

Kevin Pitt
DPhil, Speech-Language-Hearing: Sciences and Disorders, 2019
M.S., Missouri State University, 2013
B.S., University of Missouri-Columbia, 2009

Submitted to the graduate degree program in Speech-Language-Hearing: Sciences and Disorders and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Dr. Jonathan Brumberg

Dr. Holly Storkel

Dr. Nancy Brady

Dr. Robert Fiorentino

Dr. Lindsey Heidrick

Date Defended: July 15th, 2019

The dissertation committee for Kevin Pitt certifies that this is the approved version of the following dissertation:

Evaluating Person-Centered Factors Associated with Brain-Computer Interface Access to a Commercial Augmentative and Alternative Communication Device.

_____

Dr. Jonathan Brumberg, Chairperson

Date Approved: July 15th, 2019

Abstract

Purpose: Brain-computer interface (BCI) techniques may provide a link between an individual's neurological activity and communication device control, which circumvents the requirement for individuals to possess a reliable form of physical movement for augmentative and alternative communication (AAC) device access. However, while BCI technology is rapidly progressing in the laboratory setting, BCI developments are advancing largely without consideration of established AAC best practices, which are crucial for effective clinical implementation of BCI technology. For instance, BCI research largely utilize custom made software and display paradigms and view BCI as a 'one size fits all' solution. That BCI is a one size fits all solution contrasts with AAC best practice, which seek to pair an individual to an AAC device that matches their current and future profile, communication needs, and preferences. Therefore, to bring BCI research further in line with existing AAC best practices this dissertation work aims to evaluate initial and recurring person-centered factors associated with learning of motor execution-based BCI switch for accessing a commercial AAC row-column scanning paradigm.

Method: Four individuals with a diagnosis of amyotrophic lateral sclerosis (ALS) completed 12 BCI training sessions in which they made letter selections during an automatic row-column scanning pattern from a 7x5 grid. Neural signals utilized for BCI selection control were generated by motor execution during target letter highlighting. For comparison, three individuals without neurological impairment completed three BCI training sessions. During each session, participants completed approximately 20 minutes of online BCI. To assess person-centered factors associated with BCI performance and longitudinal device learning, participants completed both initial and recurring assessment measures. Initial assessment measures of an

individual's unique profile prior to BCI training included evaluation of neural signals utilized for BCI control (i.e., maximum event related synchronization amplitude (ERS), maximum event related synchronization amplitude minus predicted noise floor, and event related synchronization minus desynchronization difference; ERS-ERD), along with screening of cognitive factors, physical motor abilities, and motor imagery skills via the ALS-Cognitive Behavioral Screen, BCI screener (Pitt & Brumberg, 2018b), ALS-Functional Rating Scale, Bimanual Fine Motor Function, and Manual Ability Classification System. Recurring measures were taken during each BCI training session to evaluate changes associated with longitudinal BCI performance, and included measures of fatigue, motivation, time since last meal, device satisfaction, level of frustration with device control, mental and physical effort, and overall ease of device control.

Results: Three out of four participants demonstrated either BCI performance in the range of neurotypical peers, or an improving BCI learning trajectory across sessions. However, while BCI learning trajectories for row-column scanning BCI device were variable both between and within participants for those with ALS, findings indicate that approximately five sessions were needed to generally characterize an individual's learning trajectory during motor execution-based BCI trials. Regarding participant profiles, cognitive screening revealed that the two participants presenting with a suspicion for cognitive impairment achieved the highest levels of BCI accuracy, with their increased levels of performance being possibly supported by largely unimpaired motor skills. In addition, while scores for the cognitive section of the BCI screener were high, the two participants who did not demonstrate a consistent learning trajectory each missed one point in the area of attention and working memory, and one point in the area of cognitive motor learning and abstract problem solving. As expected, prior to BCI use, the greatest amplitude for each neurophysiological measure was generally associated with the

highest levels of BCI accuracy. However, this finding was not consistent across sessions as the participant demonstrating the lowest amplitudes prior to BCI performance presented with the highest amplitudes during BCI control. Furthermore, when evaluating neurophysiological measures across sessions, a significant correlation between left hand peak ERS and BCI performance was identified for one participant. Finally, ERS-ERD measure remained highest for the participant achieving the highest level of BCI accuracy and was significantly correlated to BCI performance for the participant achieving the second highest BCI performance levels. For recurring number scale-based recurring measures: 1) ratings of motivation were high for all participants with ALS. However, motivation ratings significantly decreased across sessions for two participants, 2) while satisfaction ratings were positively correlated to BCI performance for two participants, satisfaction ratings for the other two participants were primarily driven by perceived levels of frustration, and 3) mental effort ratings significantly decreased across sessions for one participant along with improved BCI performance, and overall mental effort ratings showed a moderate negative trend with BCI performance for two participants.

Conclusion: Overall findings support that (motor) imagery-based BCI switch access to a commercial AAC row-column scanning paradigm may be feasible for individuals with ALS, and that clinical decisions regarding BCI suitability may be informed through approximately 5 BCI training sessions, when using motor execution as a BCI control strategy. Furthermore, while generalization of findings is limited due to the small sample size, results provide multiple directions to help facilitate BCI's clinical transition by informing BCI assessment and intervention procedures. Regarding BCI assessment, findings provide early guidelines governing the length of device trials for BCI paradigms based on motor execution, and support 1) ideally beginning BCI intervention before severe deterioration of physical motor abilities to facilitate

BCI access across the disease course, facilitate BCI success, and support those with cognitive impairments, 2) further research into the development of BCI specific assessment tools, including neurophysiological measures of ERS and ERS-ERD difference to help standardize procedures for identifying factors related to BCI control. Findings relevant to BCI intervention include 1) incorporation of communication tasks beyond copy spelling to support sustained levels of BCI motivation, 2) incorporating a range of recurring person-centered measures in evaluating BCI trial outcomes including performance accuracy, levels of satisfaction, multiple measures of fatigue, and levels of frustration due to potentially differing definitions of fatigue, and differences in factors driving levels of BCI satisfaction 3) supporting more natural levels of mental effort during the establishment of BCI control.

Acknowledgements

I would like to that Dr. Jonathan Brumberg for his mentorship, generosity, and endless patience through my doctoral program, Chavis Lickvar-Armstrong for crucial support during data collection, and along with the rest of the Speech-Language-Hearing department faculty, Dr. Holly Storkel, Dr. Brady and Dr. Fiorentino for their continued support, guidance and encouragement throughout my doctoral pursuits. Also, thank you to my boys Nathan and Thomas for not arriving before I finished data collection, and to my wife, Adrienne, for helping keep them in.

This work was supported by the Texas Woman's University Woodcock Institute Research Grant, the University of Kansas Summer Research Scholarship, the American Speech-Language-Hearing Foundation New Century Scholars Research Grant, and the National Institutes of Health (NIDCD R01-DC016343-01A1).

Table of Contents

List of Tables

List of Figures

Chapter I: Introduction

Every year, thousands of people in the United States and world-wide are diagnosed with neurologically debilitating diseases, such as amyotrophic lateral sclerosis (ALS), locked in syndrome (LIS), and cerebral palsy. These disorders can leave individuals with severe physical impairments and difficulties with expressive language and motor speech, which necessitate the use of augmentative and alternative communication (AAC) for access to communication, language, and literacy. Unfortunately, while AAC methods such as eye-gaze have been successful for enabling communication access for some individuals with severe physical impairments, some individuals remain dissatisfied with current AAC options (Kageyama et al., 2014), and all traditional AAC access require some form of physical movement for device (e.g., eye control, limb control), preventing individuals with severe physical impairment from successfully accessing conventional AAC techniques.

Brain-computer interfaces (BCIs) use electroencephalography (EEG) to provide a link between an individual's neurological activity and AAC device control (BCI-AAC; e.g., Brumberg, Pitt, Mantie-Kozlowski & Burnison, 2018; Pitt, Brumberg, Burnison, Mehta & Kidwai, in review). This EEG connection circumvents the requirement for individuals to possess a reliable form of physical movement for communication access. While the idea of controlling a computer device via brain signals alone may seem like science fiction, BCIs have recently become commercially available, (i.e., the intendiX ® P300 Speller; g.tec medical engineering). However, while BCI technology is rapidly progressing in the laboratory setting, BCI performance is highly variable (Ahn & Jun, 2015; Kasahara, DaSalla, Honda, & Hanakawa, 2015; Zhang et al., 2016), and there have been few attempts for their translation into clinical practice, and limited interest from AAC professionals and commercial partners (Pitt, Brumberg,

& Pitt, in press). Barriers to BCIs clinical adoption are in part due to continued problems associated with BCI reliability (e.g., Marchetti & Priftis, 2015; Vansteensel et al., 2017) and set up requirements (e.g., Blain-Moraes, Schaff, Gruis, Huggins, & Wren, 2012; Zickler et al., 2011). However, the translation of BCI technology into the clinical setting is further impeded by a general lack of consistency between AAC best practices and BCI procedures. Currently, BCI paradigms largely utilize custom made software and display paradigms for signal elicitation. Furthermore, current research paradigms view BCI as a 'one size fits all' solution, focusing only on the assessment of one or two devices, instead of across a full range of BCI systems such as P300, evoked potentials, and motor (imagery), in addition to commercial AAC options such as eye-gaze. This approach contrasts with clinical best practices, which seek to pair an individual to an AAC device that matches their current and future profile, communication needs, and trial-based preferences (e.g., Pitt & Brumberg 2018a). These described differences between BCI-AAC display paradigms and evaluation procedures may ultimately hinder the clinical translation of BCI technology (Pitt et al., in press). Therefore, as switch input methods are a commonly utilized for traditional AAC access, this dissertation study aims to bring BCI research further in line with existing AAC practices by utilizing a motor-execution-based BCI switch to access a commercial AAC display, along with exploring guidelines governing BCI device trials, and evaluating initial and recurring person-centered factors associated with BCI learning and satisfaction.

In the following sections a background is provided on the five most common BCI methods including auditory and visual P300, auditory and visual evoked responses, and motor (imagery), along with a discussion of differing person-centered factors influencing BCI-AAC device use (e.g., attention, working memory, motor imagery skills), and the heterogenous

profiles of individuals who may use BCI for AAC access. These sections aim to provide foundational knowledge in BCI implementation necessary for understanding how BCI fits into existing clinical AAC frameworks.

1.1 BCI-AAC Devices and Predictors for Use

There are a variety of BCI-AAC methods which may be used for communication access, with successful outcomes for each BCI modality being supported by a range of different person-centered factors. The following section provides an overview of primary visual and auditory-based non-invasive BCI-AAC techniques. Each section will highlight a different BCI device, outlining how devices outcomes are correlated to varying person-centered factors. Identifying how person-centered factors correlate and influence BCI performance is a growing area of research and is critical for understanding variations in BCI performances (e.g., Ahn & Jun, 2015). For an in-depth review of both visual and auditory BCI methodologies and person-centered factors associated with BCI use, see Akcakaya et al., (2014), Brumberg, Pitt, & Burnison, (2018), Pitt & Brumberg (2018a) and Rezeika et al., (2018).

1.1.1 P300-based BCI Systems

The visually-based P300 BCI system (e.g., Donchin, Spencer, & Wijesinghe, 2000; Farwell & Donchin, 1988) is the most mature BCI technique and will likely be the first to enter clinical practice with a P300-BCI device already commercially available (i.e., Intendix Speller; g.tec medical engineering). P300-based BCIs utilize a brain signal known as the P300 event-related potential, which is a brain response to the presentation of an oddball (rare) stimulus among frequent distractors. The user interface for P300-based BCI spellers commonly incorporates a grid display (e.g., 6 x 6) including letters, numbers and symbols. To elicit the

P300 response, the individual using the BCI device focuses their attention on a target item they wish to select, while all items within the display are highlighted in a random order, commonly by changing the items from grey to white or a color. The P300 signal occurs approximately 300 ms after the target (rare/oddball) stimulus is highlighted, in comparison to non-target items. The BCI then identifies which grid item is associated with the P300 event and identifies that item for selection (Brumberg, Pitt, Mantie-Kozlowski, & Burnison, 2018). The P300 grid display may further be adapted to support an individual's oculomotor abilities by presenting P300 gird items sequentially in a location matching the individual's oculomotor abilities. For instance, for those with limited horizontal and vertical eye movement, items originally presented in the grid formation can be sequentially presented, in a random order, from the central screen location (e.g., rapid serial visual presentation paradigms; Oken et al., 2014; Pitt & Brumberg, 2018a). Alternatively, during auditory-based P300 paradigms the individual is listening for an oddball target among frequent distractors. This methodology can be used for binary (yes/no) selection via attending to one of two auditory streams (e.g. attending to a "yep" target among "yes" presentations in the right ear versus "nope" and "no" in the left; Hill et al., 2014). However, these devices are a less mature technology than their visual counterparts.

Positive outcomes for visual P300 BCIs performance are linked to a range of factors such as: 1) attention and vigilance (Oken, Memmott, Eddy, Wiedrick, & Fried-Oken, 2019), including an individual's ability to rapidly update their selective attention to focus on a new target stimulus (Geronimo, Simmons, & Schiff, 2016; Riccio et al., 2013), 2) cognitive alertness and memory as indicated by a negative correlation between theta band power and BCI performance (Mak et al., 2012), 3) an individual's oculomotor control to employ an overt attention strategy (i.e., fixating eye gaze upon desired target for selection in contrast to using peripheral attention; Arico et al.,

2014; Brunner et al., 2010; Halder, Takano, & Kansaku, 2018), 4) working memory (Sprague, McBee, & Sellers, 2016), 5) visual perception (Fried-Oken, Mooney, Peters, & Oken, 2013; McCane et al., 2014), 6) motivation (Nijboer, Birbaumer, & Kubler, 2010; Nijboer et al., 2008), 7) mood (Nijboer et al., 2008), 8) executive function skills (e.g., as assessed by measure of resting heart rate variability; Kaufmann, Vogele, Sutterlin, Lukito, & Kubler, 2011), 9) cognitive ability (Geronimo et al., 2016) and general intelligence (Sprague et al., 2016; c.f., Hammer, Halder, Kleih, & Kübler, 2018), 10) levels of concentration (da Silva-Sauer, 2016), 11) amplitude of the negative (N2) peak prior to the P300 (Halder et al., 2013; Mak et al., 2012), 12) P300 amplitude (Mak et al., 2012; Oken et al., 2018) and signal to noise ratio (Artzi & Shriki, 2018), and 13) ability to learn (Hammer et al., 2018).

Limiting factors for P300-BCI performance include 1) device workload and fatigue (Kathner, Wriessnegger, Muller-Putz, Kubler, & Halder, 2014; Oken et al., 2018), 2) boredom (Oken et al., 2018), 3) a history of seizures due to the flickering nature of the stimuli, though this risk is reduced compared to steady state visually evoked potential methods due to the flashing stimuli changing location (Pitt & Brumberg, 2018a), 4) pharmaceutical effects (Meador, 1998), 5) decreased food consumption (Geisler, 1990), which may negatively impact individuals' cognitive performance, and 6) positioning factors impeding posterior EEG electrode recordings (e.g., Fried-Oken et al., 2013), as parietal and occipital regions of the brain are crucial areas involved in generating P300 responses (Ikegami, Takano, Wada, Saeki, & Kansaku, 2012). More specifically, peak P300 amplitudes recorded over posterior areas of the scalp positively correlate with visual P300 BCI performance when compared with amplitudes recorded from fronto-central electrodes for individuals with ALS (Sugata et al., 2016). In addition, it is also important to note the requirements for P300-BCI use may differ between auditory and visual P300 devices, though

the foundational concepts remain the same. For instance, while motivational factors do positively correlate to auditory P300 amplitudes (Baykara et al., 2016), auditory P300-BCIs may be associated with increased training times (Nijboer et al., 2008), and an increased cognitive load (Klobassa et al., 2009; Kubler et al., 2009) as, similar to existing auditory AAC strategies, auditory P300 systems require mapping of the visual grid-based system into an auditory format (e.g., listening for an item location).

1.1.2 Evoked Potential-based BCI Systems

Evoked potential-based BCI paradigms use steady state EEG rhythms, which are physiological responses to a driving input stimulus (Lopez, Pomares, Pelayo, Urquiza, & Perez, 2009; Regan, 1989) such as a strobe, for selecting items from an AAC device. A user interface for a steady state visually evoked potential (SSVEP)-based BCI (e.g., Sutter, 1992) incorporates items flickering at a different rate (e.g., 12 thru 15 Hz). For instance, the Shuffle Speller SSVEP-based BCI interface (Higger et al., 2017) incorporates six strobing stimuli all flickering at different rates. Each flickering stimuli is associated with a specific box on the graphical display, which each contain different letters. During BCI control, if the individual focuses their attention on one item (e.g., 12 Hz flickering stimulus), ideally with an overt attention strategy (e.g., Brumberg, Nguyen, Pitt, & Lorenz, 2018), the EEG signal over posterior electrodes will contain a heightened amplitude (Muller-Putz, Scherer, Brauneis, & Pfurtscheller, 2005) and greater temporal correlation (Lin, 2007) to the 12 Hz stimulus in comparison to other stimuli. This target item will therefore be identified by the BCI for selection. In this Shuffle Speller paradigm, boxes are selected sequentially until one final letter remains for word spelling. The consistent flicker of the SSVEP paradigm is in contrast to the P300 interface, which highlights each item in the grid on multiple occasions and requires the individual to identify each time the target item becomes

highlighted. In a similar manner to SSVEP, auditory steady state response (ASSR)-based BCIs (e.g., Lopez et al., 2009) requires the user to attend to a sound stream containing amplitude modulated, or frequency modulated stimuli (e.g. a right monoaural 38 Hz modulation, 1000 Hz carrier tone presentation in conjunction with a left monoaural 42 Hz modulation, 2500 Hz carrier tone). The frequency of the sound stream to which the individual attends will be amplified in the EEG signal, allowing for a binary choice selection. However, to date, there is currently limited research about the application of ASSR to individuals with severe physical impairments.

Varied person-centered factors are associated with SSVEP-BCI outcomes, with performances being positively supported by factors such as 1) oculomotor control for implementation of an overt attention strategy (e.g., Brumberg, Nguyen, Pitt, & Lorenz, 2018; Kelly, Lalor, Finucane, McDarby, & Reilly, 2005; Peters et al., 2018; Zhang et al., 2010), though SSVEP devices may be adapted by placing icons in areas which suit an individual's oculomotor strengths (e.g., Allison et al., 2008; Brumberg, Nguyen, Pitt, & Lorenz, 2018), 2) for visualization of the graphical display (Pitt & Brumberg, 2018a). However mental workload (e.g., attention and working memory) demands may be decreased for SSVEP-based BCIs in comparison to P300 BCI systems (Combaz et al., 2013), possibly as active decisions about whether a novel stimulus are presented are not required (Brumberg, Pitt, Mantie-Kozlowski, & Burnison, 2018). This decrease in cognitive load further limits the negative impacts of fatigue on BCI control for neurotypical adults (Volosyak, Valbuena, Luth, Malechka, & Graser, 2011). Similar to P300 methods, positioning factors impeding posterior electrode recordings (Daly et al., 2013), uncontrolled head and neck movements (Daly et al., 2013; Sutter, 1992), and medications effecting cognitive performance may impede successful BCI use. Additionally, it is possible that the flickering visual stimuli may trigger a seizure event (Volosyak et al., 2011), and

seizure history should be considered prior to device selection. However, seizures are not reported for auditory-based BCI devices utilizing evoked potentials (Higashi, Rutkowski, Washizawa, Cichocki, & Tanaka, 2011).

1.1.3 Motor (imagery)-based BCI Systems

The focus of this dissertation will be motor-based BCI techniques, which use the neural activity resulting from imagined or executed movements to control communication devices (e.g., Blankertz et al., 2006). While this style of BCI technique is associated with increased training times in comparison to sensory-style devices such as the P300, and SSVEP (Geronimo et al., 2016; Mak & Wolpaw, 2009; Nijboer et al., 2010), motor imagery-based BCIs have multiple potential benefits over their sensory counterparts by providing access to a versatile range of user interfaces. Further with BCI training, motor (imagery) BCI methods may potentially provide increased selection and communication rates due to a decreased number of trial repetitions being required to elevate the brain signal above the environmental noise, and that sensorimotor activity is generated independently of the BCI graphical interface (e.g., the individual does not have to wait for the novel item to be highlighted). More precisely, motor (imagery)-based BCIs decode modulations of the sensorimotor rhythm which is either time locked to a given event (i.e., event related desynchronization (ERD) and event related synchronization (ERS)), or continuously. When time locked to an event, motor (imagery) BCI techniques may allow access to display and paradigms utilized by commercial AAC devices, such as single switch or multiple switch methods for communication access of a Tobii-Dynavox page set (e.g., Brumberg, Burnison & Pitt, 2016). More specifically, commercial AAC displays are commonly accessed through a switch, either in a single switch row-column type paradigm, or a multi switch system (e.g., pressing one switch advances the selection cursor, and a second switch makes a selection). While

BCI switch access is outlined in more detail below in see section 1.3.3, in a BCI context, left hand, right hand, and feet movements may be used to provide multiple switch inputs for an AAC system. In addition, the changes in the sensorimotor rhythm can be decoded by the BCI continuously. When sensorimotor signals are decoded in a continuous manner a real time 'mouse' cursor type interface may be controlled (e.g., right hand imagery moves the cursor to the right, left hand imagery to the left; Brumberg, Pitt & Burnison, 2018). Generally, ERD and ERS can be viewed as a decrease or increase in power in a given frequency band, following a specific event such as motor imagery or execution. ERD and ERS are due to either increased synchronization (i.e., ERS) or de-synchronizations (i.e., ERD) of the oscillation rate of neuronal populations (Pfurtscheller & Da Silva, 1999). When the brain is at rest and not actively performing cognitive-motor tasks it idles at a rate of approximately 8-13Hz and the neuronal oscillations are synchronized (ERS). Therefore, the ERS is characterized by increase in power in this 8-13 Hz frequency band which can be recorded via EEG. The 8-13 Hz frequency band is known as alpha when measured over central and posterior cortex, or 'mu' when measured over the sensorimotor cortex, and while the exact origin of alpha rhythms are currently unknown, it is thought to play a role in inhibitory cortical processes (Pfurtscheller & Da Silva, 1999). In contrast to ERS, when the thalamocortical systems become excited during cognitive-motor performance, alpha band power decreases in the EEG signal. This decrease in power, when time locked to a given event, is known as ERD, and is marker that cortical areas are activated in processing cognitive, sensory and/or motor based information (Pfurtscheller & Da Silva, 1999). Therefore, imagined and actual motor movements result in desynchronization of the mu band, and lower beta bands over sensorimotor areas. In the context of BCI control, ERD can be detected by the BCI after an individual has performed an imagined or an attempted movement

(e.g., Kübler et al., 2005; Neuper, Müller, Kübler, Birbaumer, & Pfurtscheller, 2003; Obermaier, 2003). The presence of the ERD signal can then be translated into a binary computer command. For instance, during this investigation the presence of ERD will trigger a BCI to select an icon currently highlighted on the AAC display during automatic scanning.

While ERD describes changes in sensorimotor activity that is related to a given event, such as an imagined movement following icon highlighting, sensorimotor modulations may also be decoded continuously. This continuous method of BCI decoding allows for access to a range of versatile interfaces such as real-time 'mouse' cursor control (e.g., Brumberg, Pitt, & Burnison, 2018; Wolpaw & McFarland, 2004), or spelling-based interfaces such as the Berlin BCI (Blankertz et al., 2006). During a continuous BCI cursor control paradigms, different imagined movements may move a cursor in different directions (e.g., left hand imagery moves the cursor to toward the left). In a communication context, this type of access method may be highly versatile, allowing for section of letters or words placed in different onscreen locations (Miner, McFarland, & Wolpaw, 1998; Vaughan et al., 2006).

Motor (imagery)-based devices are not reliant upon visual presentation paradigms that incorporate "flashing" stimuli such as the P300 and SSVEP. Therefore, while attention to task performance and online feedback remains important for motor BCI control (Geronimo et al., 2016; Halder et al., 2011; Hammer, Kaufmann, Kleih, Blankertz, & Kubler, 2014; Zhang et al., 2016), motor imagery BCIs may support individuals with impairments in selective attention (Pitt & Brumberg, 2018a). However, in contrast to P300 and SSVEP, motor (imagery) BCI control requires sensorimotor modulations, which may not be present for 15-30% of individuals within the general population (Vidaurre, 2010; Blankertz et al., 2010). While the exact reason for why these individuals do not produce a recordable sensorimotor rhythm is unknown, it is thought to

be related to anatomical differences, such as angles of the brain's gyri and sulci (e.g., Thompson, 2018). When a recordable EEG sensorimotor rhythm is present, multiple electrophysiological measures are correlated with motor (imagery) BCI success including the amplitude of the sensorimotor rhythm over electrode locations C3 and C4 during rest with eyes open for both neurotypical individuals and those with ALS (Ahn, Cho, Ahn, & Jun, 2013; Blankertz et al., 2010; Geronimo et al., 2016; Sannelli, Vidaurre, Müller, & Blankertz, 2019). In addition, gamma (>40 Hz), and theta (4-8 Hz) band powers are correlated to BCI success because they are associated with attentional control and cognitive processes (Ahn, Cho, Ahn, & Jun, 2013; Grosse-Wentrup & Schölkopf, 2012), and alertness (Mak et al., 2012). Specifically, for neurotypical adults, frontal and occipital gamma band powers are positively correlated, and centro-parietal regions negatively correlated to an individual's ability to modulate the sensorimotor rhythm during motor imagery (Grosse-Wentrup & Schölkopf, 2012; Grosse-Wentrup & Schölkopf, 2013). In addition, during rest, a positive correlation for frontal and frontal midline gamma is indicative of motor imagery BCI success (Ahn, Ahn, et al., 2013). Similarly, prior to motor imagery performance, frontal and posterior-parietal theta band powers are correlated to BCI outcomes for neurotypical participants. However, while Ahn, Cho, Ahn, & Jun (2013), found a negative correlation between theta band power and BCI performance, this was not replicated by Bamdadian, Guan, Ang, & Xu (2014), who found a positive correlation between theta levels and BCI success (see Shu et al., 2018 for review). Finally, Shu et al., (2018) found that a cortical activation strength, defined as the sum of band powers over the right and left hemisphere during motor imagery performance, predicted BCI performance for a single switch BCI system for individuals following stroke.

Outside of neurophysiological EEG measures, motor imagery BCI performance is positively correlated to an individual's ability to perform first-person motor imagery (mentally recreating the action, like you were physically performing it) versus third person imagery skill (visualizing yourself performing the action from across the room; Neuper, Scherer, Reiner, & Pfurtscheller, 2005), as while both first person and third person imagery modalities may activate motor areas (Hétu et al., 2013; Neuper et al., 2005), third person imagery is associated with less clear EEG topographies (Neuper et al., 2005).

Studies identified a positive relationship between self ratings of first person motor imagery performance and BCI accuracy for neurptypical adults (i.e., Vuckovic, & Osuagwu, 2013; Marchesotti, Bassolino, Serino, Bleuler, & Blanke, 2016), however these studies used self-ratings to measure motor imagery abilities. The utility of self ratings in motor imagery assessment (e.g., a rating of 1 = very hard to feel, thru 7, very easy to feel; Gregg, Hall, & Butler, 2010), is currently unclear (Rimbert, Gayraud, Bougrain, Clerc, & Fleck, 2019), possibly due to task differences between studies (i.e., left vs right hand imagery; Vuckovic, & Osuagwu, 2013; Marchesotti et al., 2016, right hand imagery versus rest; Rimbert et al., 2019), and difficulties in self evaluation of motor imagery performance (Rimbert et al., 2019). Beyond first person imagery ratings, other factors that are positvely correlated to motor imagery BCI perforamnce include: performance on mental chronometry tasks (e.g., whether the time to physically perform five hand clasps matches the time it took the individual to mentally recreate five hand clasps; Marchesotti et al., 2016) and frequency of hand and arm movement, if not paralyzed (Randolph, Karmakar, & Jackson, 2006; Randolph, Jackson, & Karmakar, 2010; Rimbert et al., 2019), emotional stability (Bobrova, Reshetnikova, Volkova, & Frolov, 2018), in addition to confidence mastery for both neurotypical individuals and those with ALS (Ahn, Cho, Ahn, & Jun, 2018;

Nijboer et al., 2010) and other motivational factors such as challenge (Kleih et al., 2010; Nijboer et al., 2010), and comfort with technology (Burde & Blankertz, 2006). In contrast, reaction time (Darvishi, Abbott, & Baumert, 2015), fear of incompetence (Friedrich, Scherer, & Neuper., 2013; Kleih et al., 2010; Nijboer et al., 2010) and an individual's level of tension/frustration (Jeunet, N'Kaoua, Subramanian, Hachet, & Lotte, 2015) are negatively correlated to performance. Further though, high levels of confidence may be beneficial in BCI control, it may also impair performance (Witte, Kober, Ninaus, Neuper, & Wood, 2013) by increasing levels of cognitive effort, which impede 'effortless' BCI mastery (Witte et al., 2013). Furthermore, while motor areas such as the supplementary motor area (Halder et al., 2011) are linked to motor imagery BCI control, an individual's functional limb motor skills are not currently thought to correlate to motor imagery BCI performance (Geronimo et al., 2016; Kasahara et al., 2012), as neurological activity for individuals with ALS during imagery may still parallel that of neurotypical peers (Lule et al., 2007; see section 1.2.3 for a review).

It is important to note, that learning motor imagery learning is similar to learning physical actions (Wander, 2013; Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002), with the early stages of motor learning are linked to a range of cortical networks associated with cognitive processes including attention and abstract learning (Sigrist, Rauter, Riener, & Wolf, 2013; Wander, 2013). This, in addition to working memory and visuospatial skills (Marinelli, Quartarone, Hallett, Frazzitta, & Ghilardi, 2017), may play an important role in visuomotor adaption during motor learning (Seidler, 2012). The later stages of motor learning are associated with refining and automatizing the learned action through error detection and correction processes (Sigrist et al., 2013). Similarly, motor imagery BCI performance may be affected by a range of factors including: one's ability to learn independently (Jeunet, Jahanpour, & Lotte,

2016), concentration (Hammer et al., 2012), an individual's ability to self-regulate the appropriate allocation of cognitive resources (Kleih & Kubler, 2015), such as attention (Geronimo et al., 2016; Halder et al., 2011; Jeunet, N'Kaoua, & Lotte, 2016; Zhang et al., 2016), and working memory (Halder et al., 2011; Zhang et al., 2016), visuomotor coordination (Hammer et al., 2012; Hammer et al., 2014), visuospatial skills (Jeunet et al., 2016; Jeunet et al., 2015; Jeunet, N'Kaoua, & Lotte, 2016; Zhang et al., 2016), abstract reasoning to reflect upon performance (Jeunet et al., 2015), fatigue (Myrden, 2015), which may be increased for individuals with severe physical impairment due to factors such as swallowing difficulties (Kasahara et al., 2012), ability to complete abstract reasoning tasks to reflect on imagery performance (Jeunet et al., 2015) and executive function for switching between different imagined movements (Geronimo et al., 2016), and monitoring performance (Zhang et al., 2016).

The role of these cognitive and sensory-motor interactions in motor imagery BCI success are additionally supported by a range of imaging studies, with brain activations, networks, and grey matter volumes that discriminate high versus low aptitude neurotypical users of motor imagery BCIs. Utilizing functional magnetic resonance imaging (fMRI) techniques, Halder et al., (2011) found increased activations in supplementary motor areas for individuals who had high aptitude in BCI control. Furthermore, fronto-parietal attention networks, such as the inferior parietal lobe (Zhang et al., 2016), and right middle frontal gyrus (including the dorsolateral prefrontal cortex; Halder et al., 2011), are implicated in successful BCI control due to their role in allocating high-level cognitive resources (Zhang et al., 2016). Additional MRI techniques also identified grey matter volumes of the supplementary motor area, supplementary somatosensory area, and dorsal premotor cortex (Kasahara et al., 2015), and white matter structures such as the corpus collosum, cingulum (right hippocampus), left cerebral peduncle, right posterior corona

radiata, and superior fronto-occipital fascicle in BCI control (Halder et al., 2013). This may be due to the dorsal premotor cortex acting as a hub for the interaction of cognitive-motor behaviors (Kasahara et al., 2015) and the role of the identified white matter structures in cognitive processes, in addition to connecting motor and somatosensory regions (Halder et al., 2013). However, many of these cortical areas may become impaired during neurodegeneration. Therefore, how long-term training programs not only influence BCI performance, but also the underlying neural mechanisms of BCI control is an important area of future research (Halder et al., 2013).

1.1.4. Extrinsic Factors

Along with intrinsic factors influencing BCI performance multiple extrinsic factors must also be considered for BCI-AAC use to ensure BCI approaches are focused on achieving individuals' communication goals (e.g., O'Keefe et al., 2007; Moghimi, Kushki, Guerguerian, & Chau, 2013), along with improving quality of life, and increasing social participation in their preferred activities and environments (Beukelman & Mirenda, 2013; Sexton, 2015). Sources of electrical noise (e.g., from air conditioners, muscle movements) are a common hurdle in accurate EEG implementation as they obscure or destroy the brain signals that are decoded by the BCI (Chavarriaga et al., 2017; Pitt & Brumberg, 2018a). Artifacts can be caused by varying environmental sources such as electrical interferences of power lines, lights, computers, TV and radio stations, cardiac pacemakers, ventilators and air conditioning. Methods such as filtering, sampling, and averaging may be used to limit artifacts (Abdulkader, Atia, & Mostafa, 2015). However, electrical sources may degrade EEG signals lowering BCI performance (Sellers, Kubler, & Donchin, 2006). In addition, motor artifacts from muscle activity can degrade EEG signal quality (Chavarriaga et al., 2017; Muthukumaraswamy, 2013), and while this source of

noise may be produced by spasticity and uncontrolled movements (Daly et al., 2013), motor artifacts may also be elicited by emotional expression such as laughter (Liberati et al., 2015), and environmental distractions (Brandl et al., 2015). Extending beyond the physical recording of EEG signals for BCI use, similar to commercial eye gaze systems, lighting glare or reflections may obscure a BCI visual display reducing the effectiveness of visual stimulation-based BCIs, such as the P300, and SSVEP (He, Huang, & Li, 2016).

An individual's level of support and overall goals are crucial considerations in AAC implementation, and especially for BCI to assist with factors such as troubleshooting basic environmental and technical difficulties, device set up (such as correct EEG cap placement, application of electrolyte gel), mounting, basic device operation, training, monitoring and supporting BCI use (Hill, Kovacs, & Shin, 2015; Sellers, Vaughan, & Wolpaw, 2010), and providing social reinforcement supporting BCI learning via the provision of emotionally rewarding feedback, and collaborative engagement (see Bobrova, Frolov, and Reshetnikova, (2018) and Sexton, (2015) for review). Therefore, training caregivers in BCI-AAC implementation is an important area of future research (Miralles et al., 2015; Pitt et al., in press, Wolpaw et al., 2018).

1.2 Heterogenous Profiles of Individuals with ALS

Taken together, it is clear from the previous sections that BCI-AAC techniques are not a 'one size fits all' solution, with variable cognitive-sensory-motor(imagery) factors either supporting or hindering success with a given BCI technique. In addition, identifying which BCI technique may best suit an individual is further confounded by the heterogenous cognitive-sensory-motor(imagery) profiles of individuals who may use BCI (Pitt & Brumberg, 2018b). A range of individuals may benefit from BCI technology such as those with a cerebrovascular

accident, Parkinson's disease, Parkinson-Plus syndromes, brain tumors, and traumatic brain injury (Fried-Oken et al., 2013). However, current BCI research largely focuses on individuals with ALS (Moghimi et al., 2013). The reason for this focus on those with ALS is due to factors including 1) the severity of physical impairments may prevent access to conventional AAC techniques, 2) a previously unimpaired sensory-cognitive-motor system, and 3) difficulties in studying pediatric neurophysiology (Huggins et al., 2017; Pitt et al., in press). Therefore, while research on BCI performance for different populations such as is cerebral palsy (Scherer et al., 2015; Daly et al., 2013), traumatic brain injury (Daly, Armstrong, Thomson, Andreas, & Martin, 2015), and Parkinson's disease (Kasahara, et al., 2018) is in the early stages, this dissertation research will focus on participants with an ALS diagnosis. Building upon section 1.1, in the following sections I provide an overview of ALS, describing associated cognitive-sensory-motor(imagery) profiles, which may influence clinical assessment procedures and BCI performance.

1.2.1 ALS overview and motor impairments

ALS onset is likely initiated and influenced via complex environmental-genetic (epigenetic) interactions (Paez-Colasante et al., 2015), and afflicts three to five individuals per 100,000 (Salameh, Brown, & Berry, 2015), and is described as a progressive degeneration of upper and lower motor neurons and the frontal cortex, resulting in limb and/or bulbar muscular weakness and wasting (Chiò et al., 2014). The rate of disease progression is difficult to predict due to large variability between individual presentations, and while the average life expectancy is 19 months from the time of diagnosis and 30 months from symptom onset, individuals may survive a decade or more beyond this time course (Poujois et al., 2013; Salameh et al., 2015).

The risk of this debilitating disease is 1:350 for men, and 1:500 for women (Salameh et al., 2015).

ALS has two primary subtypes based on the time of onset and degree of limb, versus bulbar (cranial nerve) involvement. When limbs are affected first it is referred to as spinal ALS, and when speech and swallowing is impaired first, bulbar ALS. Spinal ALS accounts for two thirds of onset symptoms and is commonly accompanied initially by decreased coordination of hands and feet (Salameh et al., 2015). Bulbar ALS more commonly afflicts older women (Salameh et al., 2015), and is associated with a poorer prognosis & faster disease progression than those with spinal onset (Goldstein & Abrahams, 2013). While both bulbar and spinal onset ALS subtypes typically involve both upper motor neurons (i.e. central nervous system), and lower motor neurons (i.e. nerves and peripheral nervous system), different phenotypes of ALS can occur. These phenotypes range from pure upper motor neuron disease (primary lateral sclerosis) to pure lower motor neuron disease (progressive muscular atrophy; Chiò et al., 2014). Common clinical signs of lower motor neuron involvement include; fasciculations and muscle atrophy. Upper motor neurons involvement is associated with spasticity, hyperreflexia, and emotional lability. It is important to note however, that while overt motor performance is impaired for individuals with ALS sensory modalities remain largely in tact (Salameh et al., 2015). Onset of bulbar, and/or spinal ALS motor symptoms typically occurs in the sixth decade of life (average 55 to 65 years) however, onset age is greatly variable, with clinical presentations possibly occurring during teen years or during the 8th decade of life. However, early onset (~43 years), in contrast to late onset (~57 years; Turner et al., 2003), is typically associated with improved prognosis (Poujois et al., 2013; Salameh et al., 2015).

ALS progression may leave the individual with a condition known as locked in syndrome (LIS; Plum, 1972), a state of near total paralysis accompanied by relatively intact cognition. Three categories of locked in syndrome include; incomplete LIS, classical LIS and total LIS (e.g., Fried-Oken et al., 2013; Plum, 1972). An individual with incomplete LIS retains their voluntary control of blinking, vertical eye, and other voluntary movements. In contrast, classical LIS is characterized by only retention of blinking and vertical eye control. Individuals without any form of voluntary motor movement are diagnosed with total LIS. Classical and total LIS are associated with the loss of all oral motor function, resulting in akinetic mutism, and the total inability to maintain oral nutrition and hydration. However, individuals in the early stages of bulbar involvement, or with incomplete ALS and LIS, may retain some oral motor movements.

1.2.2 Cognitive performance by individuals with ALS

Cognitive and behavioral deficits are present for approximately 30% of individuals with ALS (Beeldman et al., 2016), and a direct relationship between frontotemporal and parietal cortical thinning (loss of grey matter) has been associated with increased cognitive dysfunction (Chiò et al., 2014). Cognitive changes may manifest in variable clinical presentations, including relatively mild deficits in areas such as executive function (e.g. reasoning, flexibility, self-monitoring, and problem solving), working memory, visuospatial, impulsivity, theory of mind, eating habits, increased apathy, emotional lability (Goldstein & Abrahams, 2013; Woolley & Strong, 2015), and auditory selective attention (Volpato et al., 2016). These changes may be inpart due to changes in the dorsolateral prefrontal cortex, prefrontal cortex, orbitofrontal and medial prefrontal areas, with extensive fronto-temporal pathology being associated with the familial C90rf72 gene (Chiò et al., 2014), a gene associated with decreased P300 BCI performance (Geronimo, Sheldon, Broach, Simmons, & Schiff, 2017). Cognitive behavioral

dysfunctions may advance to fronto-temporal dementia, in approximately 10 to 15% of individuals with ALS (Beeldman et al., 2016; Chiò et al., 2014). The prognosis is worse for individuals with fronto-temporal dementia in comparison to individuals with ALS and cognitive impairment. Currently, the trajectory of cognitive decline across the disease course is under debate, and while some studies have demonstrated clear evidence of cognitive decline over time (Crockford et al., 2018), there are conflicting findings (e.g., Woolley & Strong, 2015), possibly due to difficulties in assessment of cognition for individuals with severe motor impairments.

1.2.3 Motor imagery performance by individuals with ALS

Completing motor imagery tasks parallels physical movements, with motor imagery performance recruiting similar cognitive-sensory-motor neural networks to physical task performance such as the pre-motor cortex, supplementary motor area, parietal cortex, and regions of the basal ganglia which are linked to the selection of motor programs (Hétu et al., 2013). However, some functional connectivity differences may exist between actual and imagined actions. For instance, the role of primary motor cortex in motor imagery is still unclear. Specifically, while transcranial magnetic stimulation methods indicate increased excitability of motor cortex during imagery (Loporto et al., 2011), and primary motor cortex activity is reported during fMRI studies of individuals with ALS during imagery performance (Lule et al., 2007), in contrast to physical movements, involvement of primary motor cortex in imagery tasks may be less consistent (Hétu et al., 2013; Poujois, 2013). However, individuals with ALS may demonstrate increased recruitment of cortical areas associated with motor and motor imagery performance (Kollewe et al., 2011; Lule et al., 2007), as reflected by an increased fMRI hemodynamic response. The increase in hemodynamic response is likely a compensatory process due to neurodegeneration, and loss of inhibitory interneurons possibly leading to hyperactivation

of residual neurons (Lule et al., 2007), especially to support function of the most impaired limb (Poujois et al., 2013). However, as the disease progresses, this increased response may give way to a reduction in motor related cortical activity (e.g., Stanton et al., 2007; Stoppel et al., 2014). This change in cortical activities across the ALS disease course supports a continuously changing sensory-motor system, with early compensatory changes, followed by the breakdown of these functional compensatory processes (Stoppel et al., 2014). However, further research is needed to characterize neurological activations across the ALS disease course (Lule et al., 2007), controlling for factors such as age and cognitive status.

That compensatory motor cortex activity is present for individuals in the early stages of ALS within motor imagery related networks similar to neurotypical individuals (Lule et al., 2007) supports findings that individuals with ALS can generate the sensorimotor modulations needed for motor (imagery)-based BCI control (e.g., Kubler et al., 2005). However, Kasahara et al., (2012) found that in comparison to neurotypical controls, the presence of the ERD was dampened for individuals with ALS, especially for those with increased bulbar involvement. Therefore, the magnitude of the ERD during motor imagery and BCI use may not be solely governed by the number or activation of surviving neural cells, but is also effected by person centered factors such as an individual's ability to recall a motor action from memory, level of fatigue, ability to concentrate on the imagery task (Kasahara et al., 2012), and type of imagery task (e.g., imagining a novel action; Halder et al., 2011). Finally, decreased performance on implicit motor imagery tasks (e.g., hand rotation tasks) is noted for individuals with ALS compared to neurotypical controls (Fiori et al., 2013). Further, Osuagwu & Vuckovic (2014) found that both implicit and explicit (i.e., tasks whether the individual is consciously/explicitly performing motor imagery) tasks produce similar time and spatial EEG characteristics for

neurotypical participants, but the tasks may utilize some slightly different neural structures for task completion (Hétu et al., 2013) with implicit tasks being possibly completed via third person motor imagery for some individuals with neuromotor impairments (Craje et al., 2010; Pitt, & Brumberg, 2018b), which may less successful than first person imagery strategies for BCI control.

1.3 Transitioning BCI into clinical practice

Non-invasive BCI access methods can provide hope and freedom to the most severely impaired individuals by overcoming the motor restrictions of conventional approaches to AAC access (Blain-Moraes et al., 2012). However, even with promising results from long-term BCI trials (e.g., 18 months; Wolpaw et al. 2018; Holz, Botrel, Kaufmann, & Kubler, 2015; Miralles et al., 2015; Sellers et al., 2010; Birbaumer et al., 1999) BCI technology is experiencing limited translation into clinical practice (e.g., Chavarriaga et al., 2017; Pitt et al., in press). Thus far, the slow transition of BCI into clinical practice is in partly due to continued problems associated with BCI reliability (e.g., Chavarriaga et al., 2017; Marchetti & Priftis, 2015; Vansteensel et al., 2016), and that the majority of BCI research is aimed at developing signal processing algorithms (Powers, Bieliaieva, Wu, & Nam, 2015). However, though development of effective BCI algorithms is crucial for improved BCI outcomes, a general lack of guidelines governing clinical BCI implementation, and a general lack of consistency between current clinical best practices for AAC and BCI research procedures further impedes the translation of BCI into the clinical setting (Pitt, et al., in press). Extending the work of Pitt et al., (in press), Brumberg, Nguyen, Pitt, & Lorenz, (2018), Brumberg, Pitt, Mantie-Kozlowski & Burnison (2018), Pitt, & Brumberg, (2018a), and Pitt & Brumberg, (2018b) the following sections review 1) feature matching assessment, 2) utilization of existing AAC devices and paradigms, and 3) incorporation of

stakeholder feedback to provide specific examples of how this project aims to facilitate the transition of BCI technology into clinical practice by building upon AAC research and best practices. For a full review of how BCI can integrate with current clinical procedures for AAC implementation see Pitt et al., (in press).

1.3.1 BCI-AAC Feature Matching

Feature matching is a widely established clinical method for AAC practice (Gosnell, Costello, & Shane, 2011) and is used to pair an individual to an AAC device, page-set, and access method that best matches the individuals current and future, cognitive, sensory, motor, and linguistic profile, needs and trial-based preferences, in addition to their environment, communication needs and levels of support (Gosnell et al., 2011; Pitt & Brumberg, 2018a). These person-centered feature matching procedures allow an individual to trial multiple AAC devices with a variety of access methods, feedback types, and graphical interfaces. This systematic evaluation ultimately leads to the selection of an AAC device that best matches each individual's unique strengths and preferences, facilitating AAC success while limiting the potential for device abandonment (Beukelman & Mirenda, 2013). A strengths-based approach is an important concept in helping ensure an effective user-device match, helping increase outcomes with the chosen AAC device (Thistle & Wilkinson, 2015). However, as described in section 1.2, individuals who may use BCI vary in their levels of sensory, motor, and cognitive ability. Taken in conjunction with the broad range of BCI techniques available (see section 1.1), a lack of feature matching-based BCI assessment guidelines means it is currently unclear what type of BCI device may best support successful communication for individuals with severe physical impairments. Effective procedures for BCI-based feature matching need to be established to facilitate individual success (Hill et al., 2015; Light & McNaughton, 2013; Pitt &

Brumberg, 2018a), and promote consistency in terminology between BCI procedures and AAC practice (Pitt et al., in press). Furthermore, during a 1995 National Institute of Deafness and Other Communication Disorders (NIDCD) sponsored forum, the study of how an individual's unique profile influences AAC success was identified as a research priority by individuals with severe physical impairments (Beukelman, & Ansel, 1995; O'Keefe et al., 2007). For BCI, the implementation of feature matching procedures will help a multidisciplinary AAC team to focus on the provision of comprehensive and person-centered services that accounts for the individuals' unique profile, in relation to the capabilities, and requirements, of current BCI technology. While existing BCI research has laid a critical foundation for the development of feature matching frameworks for BCI (e.g., Pitt, & Brumberg, 2018a; Pitt & Brumberg, 2018b), current BCI research largely focuses on predicting outcomes for one or two BCI techniques, instead of the full range of possible devices. A lack of guidelines governing BCI assessment across a full range of devices means that an individual may not be paired to their most appropriate BCI technique. Therefore, to lay the initial foundations for an AAC-style feature matching framework for BCI, Pitt & Brumberg (2018a) developed a multidisciplinary framework to guide feature matching procedures across a total of nine types of BCI devices, including considerations for sensory, motor, motor imagery, medical, cognition, and literacy assessment along with extrinsic considerations.

Currently, the development feature matching assessment procedures for BCI, especially motor imagery-based BCIs, are still in the early stages. Screening protocols can help ensure that an individual is provided with an appropriate BCI device (Ahn & Jun, 2015), and the utilization of screening protocols is an important goal for standardizing clinical and research practices for BCI (Fried-Oken et al., 2013). To fill this void in assessment, general purpose cognitive

screening protocols are intermittently utilized for participant assessment prior to BCI use (e.g. ALS-Cognitive Behavioral Screen (ALS-CBS; Woolley et al., 2010). However, while attention, tracking and word initiation portions of the ALS-CBS are linked to initial BCI performance (Geronimo et al., 2016), these protocols cannot be fully completed via binary response, making them unsuitable for some individuals who may use BCIs for communication. In addition, the tasks included in these protocols are not designed to predict BCI performance. Therefore, the developments of assessment measures with a BCI focus are necessary to illuminate the contrasting cognitive-sensory-motor(imagery) factors associated with BCI performance and learning. To date, there are only two published BCI screening protocols available. The first protocol, by Fried-Oken et al., (2013), aims to screen an individual's skill set prior to the use of an attention modulated P300-RSVP BCI speller. While an important first step in BCI assessment, this protocol does not incorporate tasks that may be valuable for matching an individual to other types of BCI technique, such as motor imagery. Thus, to support feature matching-based BCI assessment in research and clinical practice, Pitt & Brumberg (2018b) developed a screening protocol assessing a range of factors related to BCI use, such as sensory (hearing and visual skills), cognition (comprehension and orientation, following directions, attention and working memory, and cognitive motor learning/abstract problem solving), motor imagery (explicit and implicit), along with other BCI considerations including positioning, motor abilities (including oculomotor abilities), comfort with computers, motivation, fatigue, handedness, history of seizures, and level of pain. The feature matching screening protocol was found to be feasible for completion by individuals with severe physical impairment being completed in less than 60 minutes, via binary response. However, it is still unclear how levels of cognitive impairment (e.g. mild versus moderate cognitive impairments) impact BCI

performance across devices (Pitt, & Brumberg, 2018; c.f., Geronimo et al., 2016). Since this foundational assessment protocols only assess if the individual possesses certain BCI related skills, and not the skill level. In addition, current screeners do not include neurophysiological (e.g., ERD, and ERD) measures of BCI performance (e.g., Blankertz et al., 2010; Shu et al., 2018) to allow for ease of clinical implementation despite their important consideration in BCI assessment, which may limit the utility of current screening methods.

It is plausible that a screening protocol incorporating tasks tailored to evaluate key areas for BCI feature matching will improve the effectiveness of BCI assessment methods and illuminate specific areas that are crucial for feature matching evaluation across BCI types, helping increase device success, and social participation, while decreasing training times and the rate of device abandonment. However, the feature matching screening protocol by Pitt & Brumberg (2018b) is untested in relationship to BCI performance. Therefore, further testing of the screener is needed in relation to BCI control by individuals with neuromotor disorders, including the application of neurophysiological measures, to begin to assess the utility of the BCI screener in assessing person-centered strengths associated with longitudinal BCI performance, and advance research in BCI assessment. The process is made more difficult because cognitive-motor factors change rapidly in individuals with ALS. For instance, as with commercial AAC devices, BCI performance may fluctuate throughout the day, or on a day to day basis, depending upon transient factors (e.g., levels of fatigue) that may impact BCI performance (Thompson, 2018). Therefore, when considering BCI selection, BCI proficiency and transient factors impacting levels of fatigue and motivation should be considered on a longitudinal trial basis, rather than just a single point in time (Thompson, 2018).

1.3.2 Including stakeholder input in BCI development and intervention

Not involving input from stakeholders, such as individuals using AAC, family, caregivers, and AAC professionals in the development, selection, and integration of assistive technology into their daily lives, leads to a greater likelihood of device abandonment (Blain-Moraes et al., 2012). Therefore, including stakeholders in the implementation of both traditional AAC methods (e.g., Beukelman, & Ansel, 1995; O'Keefe et al., 2007; Phillips & Zhao,1993; Romski & Sevcik, 2018; Powers et al., 2015), and BCI (e.g., Blain-Moraes et al., 2012; Brumberg, Pitt, Mantie-Kozlowski, et al., 2018; Chavarriaga et al., 2017; Huggins, Wren, & Gruis, 2011; Liberati et al., 2015) is of critical importance to support successful communication outcomes, clinical service delivery (O'Keefe et al., 2007), and to ensure that AAC products meet ethical, legal, technical, and social requirements, which enhance an individual's autonomy (Nijboer, 2015). However, while recent BCI studies are beginning to explore the opinions of stakeholder feedback (e.g., Blain-Moraes et al., 2012; Holz et al., 2015; Huggins et al., 2011; Liberati et al., 2015; Pasqualotto et al., 2015; Peters, Mooney, Oken, & Fried-Oken, 2016; Kageyama et al., 2014), research in this area is limited. To date, research regarding stakeholder perspectives is generally positive (e.g., Blain-Moraes et al., 2012; Liberati et al., 2015; Miralles et al., 2015; Wolpaw et al., 2018), with 84% of individuals indicating they would be willing to wear the EEG cap to access BCI systems (Huggins et al., 2011), and that BCI technology can offer freedom, hope and connection, which fulfils an unmet need in their daily lives (Blain-Moraes et al., 2012). Furthermore, one individual with ALS indicated that BCI restored his independence, using a P300-based BCI to run his NIH-funded research laboratory and to communicate via e-mail with family, friends, and colleagues. (Sellers et al., 2010). However, stakeholders also note barriers to BCIs successful application into their everyday life such as

fatigue, effort, anxiety (e.g., due to flickering stimuli; Blain-Moraes et al., 2012), frustration (Miralles et al., 2015), discomfort and physical issues caused by wearing the EEG cap (Blain-Moraes et al., 2012), problems with set up (Blain-Moraes et al., 2012), reliance on system assistants (Wolpaw et al., 2018), and issues related to performance reliability (e.g., Holz et al., 2015; Miralles et al., 2015).

For current AAC practice, individuals with ALS report the need for AAC professionals to provide opportunities to trial a variety of AAC systems, since there is no "one best fit" for everyone (McNaughton et al., 2018). The same is true for BCI, and individuals with severe speech and physical impairments have varying perceptions of workload, comfort, ease of use, and satisfaction with a given BCI system (Peters et al., 2016). Furthermore, individuals with ALS report that visual P300 BCIs required more cognitive workload compared with eye gaze access (Pasqualotto et al., 2015), a conventional AAC access method, due to the decreased BCI selection rates, and difficulties in maintaining focus on BCI tasks during unexpected events (Blain-Moraes et al., 2012). However, in contrast, some individuals report P300-BCIs are easy to use as no precise eye movements are required (Holz et al., 2015; Kathner, Kubler, & Halder, 2015). A case study report found one individual with locked in syndrome reported global ratings of workload, fatigue, and frustration were lower for BCI use versus eye-gaze (García et al., 2017). An individual's level of comfort may additionally effect preferences for BCI use, with those who are comfortable with technology demonstrating an increased willingness to trial BCI devices (Geronimo, Stephens, Schiff, & Simmons, 2015). However, current studies evaluating stakeholder perspectives regarding factors such as device satisfaction, frustration, and levels of effort are limited, with the vast majority focusing on stakeholder opinions regarding the implementation of P300-based BCI technology and not across a range of BCI methods.

Longitudinal BCI learning influences motivational factors for neurotypical individuals (Friedrich et al., 2013) and those with ALS (Nijboer et al., 2010). Furthermore, individuals may report high levels of exhaustion during early BCI training (Friedrich et al., 2013), and some reports by individual with ALS indicate frustration and dissatisfaction with motor imagery BCI control during the early stages of motor learning (Nijboer et al., 2010). Therefore, it is important to ascertain how stakeholder attitudes on perceived levels of motivation, fatigue, frustration, effort, workload and overall device satisfaction change during motor-(imagery) BCI learning. As longitudinal changes in overall satisfaction and psychological factors (e.g., workload) are currently unclear, elucidating how associated stakeholder ratings change during the motor (imagery) BCI learning processes is necessary to ensure individuals are provided with sufficient time to learn the BCI system and make an informed decision about their BCI preference. Furthermore, evaluating how factors, such as performance accuracy, correlate to person centered factors and satisfaction over time will help identify crucial considerations for BCI assessment, informing clinical and research guidelines governing BCI trials.

1.3.3 Utilizing existing AAC paradigms and evaluating trail lengths.

Findings by Liberati et al., (2015) reveal that individuals with ALS highly value AAC devices that can adapt to their changing sensory-cognitive-motor profile, exploiting the strongest current communication channel both in the short and long term. This concept of 'ability-based' AAC design seeks to develop AAC devices that support access across the life span/disease course, and emphasizes the role of creating AAC systems that can adapt to the individuals changing needs, instead of requiring the individual to adapt to the AAC technology (Light et al., 2019). However, motor imagery BCI research focuses on imagined task performance, regardless of the individuals physical motor abilities. This narrow focus on imagined task performance does

not utilize the individuals existing motor skills, possibly decreasing motor cortex activities during task performance (e.g., Hétu et al., 2013), which may negatively impact BCI performance. Furthermore, motor execution may increase BCI performance in comparison to imagery for some BCI users (Neuper et al., 2005), especially those with decreased initial BCI performance (Sanneli et al., 2019), and while the effects on non-invasive BCI performance are unknown, invasive electrode recordings show there may be differences in cortical activities between real, attempted and imagined movements (Vargas-Irwin et al., 2018). Therefore, utilizing an individual's residual motor function for BCI control may help support improved BCI accuracies, lowering cognitive difficulties associated with performing abstract motor imagery tasks. Furthermore, physical practice may facilitate improved first-person motor imagery performance (a strategy associated with improved motor imagery-based BCI success; Neuper et al., 2005), by supporting recall of the physical action from memory (Vuckovic, & Osuagwu, 2013; Halder et al., 2011). Thus, providing timely BCI-AAC access via motor execution early in the disease course for those with progressive neuromotor disorders, before motor movements become severely impaired, may help provide a strong foundations for an individual's transition to a motor imagery strategy later in the disease course when progressive paralysis prevents physical motor movements. For instance, an individual may access a BCI-AAC system via motor execution, or multimodal AAC methods (e.g., Fager, 2018) early in the disease course, with the individual choosing their method of AAC access depending upon factors such as fatigue, motor ability, and environmental factors (e.g., the individual may choose to use BCI access when sun glare on the AAC display hinders eye-gaze access). Similar to existing AAC methods, providing BCI access early in the disease course may allow an individual to utilize the same AAC device, and access method(s) across the life span, decreasing the emotional burdens and anxieties

associated with learning a new AAC system late in the disease course (Blain-Moraes et al., 2012), and ultimately supporting BCI success (Marchetti & Priftis, 2015; Pitt et al., in press).

In addition to a focus on motor imagery BCI control, BCIs are most commonly designed with displays, presentation paradigms, and software that are lab-specific, with BCIs being largely seen as a 'last resort' instead of alongside existing AAC methods such as eye-gaze (Pitt, et al., in press). However, implementing BCI as a last resort AAC option ultimately impedes the continuity of AAC intervention across the disease course, increasing an individual's emotional struggle, and learning demands by requiring them to learn multiple forms of AAC access across the disease course (Liberati et al., 2015). Introducing BCI earlier, in conjunction with other forms of AAC practices (e.g., multimodal AAC access; Brumberg, Pitt, Mantie-Kozlowski, et al., 2018; Fager, 2018) may help promote collaborations with commercial partners and manufacturers (Ray, 2015). Efforts are under way to utilize BCI techniques to access commercial AAC paradigms and software (Brumberg et al., 2016; Scherer et al., 2015; Thompson, Gruis, & Huggins, 2014; Zickler et al., 2011).

Scanning-based AAC paradigms have a long history in traditional AAC implementation to provide AAC access to adults (e.g., Beukelman, Fager, Ball, & Dietz, 2007; Doyle & Phillips, 2009; Fager, Bardach, Russell, & Higginbotham, 2012; Fried-Oken, Mooney, & Peters, 2015), and children (e.g., Campbell, 2006; McCarthy et al., 2006) who cannot make direct item selections via methods such as touch, or eye-gaze (Beukleman & Mirenda, 2013). Broadly, during item scanning, communication items are presented by the communication device, or trained communication partner in a set pattern (e.g., sequentially in a linear order). To select an item, the individual must wait until the communication partner or device scans to the desired communication item, then perform a pre-determined action for item selection such as switch

activation (Beukleman & Mirenda, 2013). Items within the scanning display may be presented via auditory (e.g., the device or communication partner announces each item aloud) or visual (e.g., communication partner points to each item, or each item is highlighted by a red box) paradigms (e.g., McCarthy et al., 2006). A common scanning pattern is row-column scanning, during which each row of the grid is sequentially presented. Then, following row selection, each column of the selected row is presented until a final selection is made(Beukelman & Mirenda, 2013).

In parallel to commercial AAC access methods utilizing switch-based access to scanning paradigms, there is an established history of BCI research regarding the utility of BCI techniques as a form of switch (e.g., Müller-Putz, 2010; Muller-Putz, Pokorny, Klobassa, & Horki, 2013; Scherer et al., 2015; Shu et al., 2018; Solis-Escalante, 2010). Regarding the specific use of BCI to access commercial AAC scanning displays, research is limited. However, Friedrich et al., (2009), investigated motor imagery-based BCI access during an automatic scanning paradigm. Their investigation incorporated four squares arranged horizontally, highlighting each square with a yellow box for 2.5 seconds. Over a five-week period, eight neurotypical participants, one individual with ALS, and one individual with thoracic-outlet-syndrome completed ten BCI training sessions. Friedrich et al., (2009) found that BCI performance was variable both within and across participants, with the participants mean accuracy increasing from 35% (S.D. = 14) in session one, to its peak in session eight (57%, S.D. = 20, chance accuracy 25%). The highest single session accuracy was 91% in session four. The number of ‘false’ selections decreased across sessions but was significantly higher than the number of selection ‘misses’. While performance for the individual with ALS was not discussed in detail, their performance was variable. The reasons for the performance variations noted in this study are unclear, but may be

due to participant heterogeneity, and person-centered factor such as motivation, emotional state, and use of imagery strategy. For instance, one participant with 'very good' neurophysiological sensorimotor signals only achieved moderate BCI success, possibly due to work-related stress. Taken together, this study shows BCI has promise for scanning-based computer access but requires further testing on larger matrices.

The use of switch-based BCI for scanning-based access to larger AAC-Style matrices was subsequently assessed by both Scherer et al., (2015) and Brumberg et al., (2016). Scherer et al., (2015) evaluated single session BCI performance by fourteen adults with cerebral palsy during a row-column scanning paradigm incorporating a 3 by 3 display of graphical symbols (e.g., fruit). Each matrix item was highlighted by a red square for 4 seconds, with a 2 second break in-between intensifications. For BCI control participants performed either kinesthetic motor imagery or mental arithmetic (e.g., counting backwards) to make an item selection. Following item selection, an auditory beep was provided along with an animation of the item dissolving to increase feedback and participant engagement in BCI control. Results indicate that while three participants were unable to successfully control the BCI, eleven participants achieved control levels above chance levels. However, the authors discuss that limitations of the study include a lack of assessment prior to BCI training such as the participants cognitive abilities. Finally, Brumberg et al., (2016) evaluated motor imagery access to a commercial Tobii-Dynavox page set during a single training session. The scanning paradigm incorporated a 4 x 3 matrix with each graphical item highlighted by a red square for 2.5 seconds along with auditory feedback announcing the name of the highlighted element (e.g., pizza). No live interface feedback was provided during this study, and predicted online accuracy was evaluated using MATLAB software (i.e., a twofold cross validation). Six neurotypical

individuals and one individual with ALS completed the BCI training session with neurotypical participants achieving a mean of accuracy of 60% (range 55.7 to 63.55), and the individual with ALS 62.6% accuracy. However, further trials utilizing online BCI control were not performed during this study, and assessments of cognitive motor factors were not included.

The provision of BCI-based access to commercial AAC scanning paradigms provides a strong avenue for the clinical translation of BCI technology, due to clinician familiarity with switch access, and the established history of utilizing switches for scanning-based AAC access in clinical practice, in conjunction with the foundation's demonstrating BCIs utility in providing switch functions. Therefore, continued work on the feasibility of BCI switches to existing AAC devices and paradigms may encourage commercial partners to make minor modifications necessary to allow to BCI-base switch input, and place BCI in existing AAC frameworks to bolster clinician familiarity with BCI techniques. The aforementioned studies evaluating BCI access to scanning paradigms highlight the need for cognitive-sensory-motor assessment to elucidate person centered factors correlating to performance variability. Furthermore, the largely limited durations of these studies, and discussed performance variability across sessions (Friedrich et al., 2009) mean the learning trajectories of individuals using BCI switches is largely unknown, clouding guidelines governing the length of motor (imagery) BCI trials for scanning-based access. In addition, individual learning trajectories remaining largely unassessed (c.f. neurotypical performances for non-scanning-based BCI paradigms; Friedrich et al., 2013; Neuper, Schlögl, & Pfurtscheller, 1999). Therefore, the optimal length of BCI trials for research and clinical practice to select a device are currently unknown, obstructing researchers and clinicians from understanding the trajectory of BCI learning and how individuals establish

personal preference, ultimately impeding the reliable identification of factors and training strategies influencing BCI success and performance variability.

1.4 Aims

The previous sections highlighted different BCI techniques (i.e., P300, motor imagery and evoked potential methods), sensory-cognitive-motor(imagery) factors associated with BCI performance, and the unique profiles of individuals with ALS, who are commonly targeted for BCI investigations. In addition, different factors that facilitate the clinical translation of BCI technology were discussed including the importance of feature matching procedures, including stake holder input, and incorporating existing AAC paradigms into BCI research. However, research in these areas of clinical translation is still emerging, and there are still multiple gaps to address for BCIs successful integration with clinical practices. To effectively match an individual to a BCI device, factors influencing BCI success need to be identified, and assessment tools suitable for completion by individuals with severe physical impairments need to be established.

This dissertation work included a BCI switch, extending existing scanning-based BCI studies. In addition, we included a range of cognitive-sensory-motor assessments , including the BCI screener for Pitt and Brumberg (2018b) prior to BCI instruction to facilitate the clinical implementation of BCI technology and bring BCI research further in line with existing clinical procedures. The specific aims of the study are:

1) Evaluate the individual learning trajectories of four participants with a diagnosis of ALS in mastering BCI-AAC device control via a (motor)-imagery BCI switch during row-column scanning over 12 BCI training sessions.

2) Evaluate how person-centered factors measured by both initial BCI assessments (e.g., BCI feature matching screener (Pitt, & Brumberg, 2018), ALS-CBS (Woolley et al., 2010), and recurring measures (e.g., neurophysiological, effort, frustration, motivation) relate to each individual's BCI performance trajectory and satisfaction.

Chapter II: Methods

All study procedures were approved by the Institutional Review Board of the University of Kansas. Depending on the participants motor abilities, participants provided self-consent or consent via a legally authorized representative prior to engaging in all study activities.

2.1 Participants

Four Caucasian individuals with a diagnosis of ALS (participants A1-A4, ages 38.3-64.11, mean 52.3 years, 2 females, all right handed; see table 1), and three Caucasian neurotypical individuals (T1-T3, ages 23.2-60.5, mean 41 years, 2 females, all right handed) completed the study. With patient consent, names of participants were provided by faculty in the Speech-Language-Hearing departments located at the University of Kansas-Lawrence and the University of Kansas Hearing and Speech Medical Center, in addition to the ALS clinic in the Landon Center for Aging. Further, participants were recruited by the research team directly from the ALS clinic in the Landon Center for Aging, during the weekly ALS clinic.

Table 1. Participant information for those with a diagnosis of ALS

Participant Number	Diagnosis	Time since diagnosis (years.months)	Sex	Age (years. months)	Primary communication method	Medications
A1	Bulbar ALS	0.7	F	64.11	Verbal	Diabetes
A2	Spinal ALS	1.11	M	38.3	Verbal	Radicava infusions,

						Riluzole from 12/16-12/18, muscle relaxants, as needed
A3	Spinal ALS	10.4	F	48.9	Verbal and eye-gaze (as needed)	Muscle relaxants as needed
A4	Spinal ALS	3.5	M	57.8	Verbal	Riluzole 2x/day, muscle relaxants, as needed

2.2 EEG and BCI recording and data processing

EEG recordings for this investigation were collected at a sampling rate of 256Hz via a 62 active electrodes (g.HIAmp, g.tec) arranged according to the 10-10 standard (Oostenveld, 2001).. A notch filter at 58-62 Hz was utilized for removal of power line artifacts. The reference electrodes were located on the left and right ear lobes (averaged earlobe reference). During EEG set up, the participant sat comfortably in front of the computer screen.

2.2.1 Training data for BCI calibration

Prior to online BCI control, similar to calibration trials for eye gaze AAC access, BCI calibration data was collected from 90 trials, which included 60 trials of motor execution during which the individual was instructed to move either their upper or lower limbs (e.g., 30 trials of left hand and 30 trials of right-hand execution), and 30 trials of rest. Following calibration data collection, training data was processed offline using MATLAB (The MathWorks, Natick, MA) software and used for setting online BCI control parameters. Similar to current AAC assessments, the BCI calibration and online BCI control task were chosen based on participant preference, physical motor skills, and calibration results (e.g., predicted BCI accuracy), with

options for BCI selection including motor execution of either right hand, left hand, both hands, or both legs/feet motor execution.

2.2.2 BCI-AAC control

During trials of online BCI-AAC control participants completed copy spelling tasks by making letter selections from a 7x5 keyboard display including letters A-Z, space and back space similar to those available on commercial AAC devices (see figure 1). Paralleling commercial switch-based access to AAC displays, letter selections were made during an automatic row-column scanning pattern, during which the AAC device automatically advanced the selection box in a linear fashion through all possible rows in the graphical display, while the individuals remained at rest, with row selection occurring when the BCI detects an executed movement. Following row selection, the AAC device automatically advanced the selection box in a linear fashion through all possible columns, with final letter selection occurring when the BCI detects an executed movement.

Based upon previous lab procedures utilizing this scanning paradigm (see Brumberg et al., 2016 for further details), a scanning rate of 2 seconds per item with an inter-stimulus duration of approximately one second was employed. During scanning, each row was first highlighted by a blue rectangle. Upon selection each item within that row was sequentially highlighted. To indicate a selection was made the blue box briefly turned black. Neural signals used for BCI control (ERS and ERD) were modulated by motor execution of the upper (for A1, A2, and A3), or lower limbs (for A4). Paralleling AAC assessment, selection of which limb would be used for BCI control was based upon initial performance and participant preference. For instance, while unused at this time, A4 owned two knee switches for use with his recently purchased AAC device. Therefore, in addition to having less motor impairment in his lower versus upper limbs,

he wished to be consistent between use of the BCI and his physical switches to potentially increase functionality should the BCI system become a viable option for AAC access in the future.

In this BCI paradigm, to accurately select a target letter the BCI must accurately decode both "select" trial decisions during which the individual performs motor execution, in addition to "do not select/continue scanning" trial decisions, where the individual remains relaxed.

To help support motor leaning, during online BCI control, feedback was provided to the participant regarding how close the BCI was to making a selection. Similar to commercial eye-gaze AAC paradigms, this feedback was provided in the form of a circle that got smaller as the BCI algorithm detected presence of the ERD and moved toward selecting the currently highlighted item.

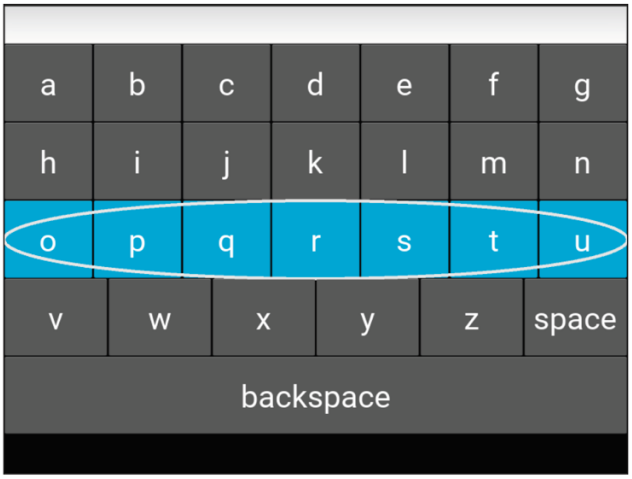

Figure 1. The motor (imagery) BCI interface, depicting the third row highlighted, and the feedback circle, in white.

2.3. BCI-AAC training sessions

Following initial feature matching-based BCI assessments (see section 2.4), participants with a diagnosis of ALS completed a total of twelve BCI training sessions. For comparison of

initial BCI performance, individuals without neurological impairment completed three BCI trainings. During each session, all the participants completed approximately 20 minutes of online BCI control consisting of total of approximately 300 trials per session. For participants A1 and A2, training sessions were completed in the laboratory setting (i.e., an electrically shielded booth, with the door open to allow for communication with the participation throughout BCI trials). However, due to travel restrictions, BCI sessions for A3 and A4 were in a quiet room, free from disturbance, in their home setting.

2.4 Assessment of person-centered factors

2.4.1 Initial BCI assessment measures (non-EEG based)

Prior to the first BCI training session the following assessment measures were completed to ensure participant suitability to undertake study procedures and evaluate neurophysiological and psychological factors related to BCI control.

1) **ALS-Cognitive Behavioral Screen:** The ALS-CBS (Woolley et al., 2010) is a general-purpose cognitive screening tool used in assessing the areas of attention, concentration, tracking and monitoring, and initiation and retrieval. An ALS-CBS score of less than 17/20 indicates a concern for cognitive impairment, with a significantly increased concern for scores less than 12.
2) **Feature matching-based BCI screener**: As a first step in the development of feature matching based BCI screeners, the BCI assessment protocol by Pitt & Brumberg (2018b) aims to assess if participants possess core-BCI related skills. The maximum score for the cognitive portion of the screening protocol is 24, and for the motor imagery section 15. In addition, assessment of oculomotor function along with descriptive assessment of the upper and lower limbs is collected. Further, a subtest assessing visuospatial skills via

mental shape rotation test was also completed with a maximum score of 5.

3) **ALS-Functional Rating Scale**: The ALS-FRS (Cedarbaum & Stambler, 1997) is a commonly utilized clinical assessment of an individual's function physical motor abilities. To complete the assessment protocol, individuals rate their functional motor abilities on a scale of 0 (severely impaired) to 4 (normal) in the 10 areas of speech, salivation, swallowing, handwriting, cutting food and handling utensils, dressing and hygiene, walking, climbing stairs, and breathing. The maximum score for the protocol is 40, with higher scores demonstrating greater levels of motor functionality.
4) **Bimanual fine motor function (BFMF) and Manual ability classification system (MACS):** The BFMF (Beckung & Hagberg, 2002) and MACs (Eliasson et al., 2006) aim to assess level of activity limitation due to motor impairment of the upper limbs with level 1 indicating minimal restriction, through 5, highly limited function, and may provide complementary information regarding assessment of motor function (Elvrum et al., 2016). As the scales were developed for children with cerebral palsy, wording was adapted to ensure appropriateness for adults

2.4.2 Neurophysiological assessment measures (EEG-based)

Amplitude of EEG sensorimotor rhythm at rest and during motor execution:

As described in section 1.1.3, motor (imagery)-based BCIs decode neural activity related to the performance of physical or imagined movements. Specifically, in the context of this row-column scanning based BCI, increasing neural synchrony in the alpha band at rest (known as the ERS) will support the BCI to continue scanning, with presence of the ERD during motor execution, prompting the BCI to make a selection. However, approximately 15-30% of individuals do not present with the sensorimotor rhythm (ERS and ERD) signal necessary for

motor (imagery) BCI control (Vidaurre & Blankertz, 2010; Blankertz et al., 2010), possibly due to anatomical differences (e.g. Thompson, 2018). Therefore, presence of the sensorimotor rhythm (ERS and ERD) was screened prior to BCI performance using procedures based upon Blankertz et al., (2010), and Shu et al., (2018). Specifically, presence of the sensorimotor rhythm was calculated from the 30 'rest' trials obtained during EEG calibration sessions. ERS, sensorimotor rhythm amplitudes were ascertained by fitting an exponential Gaussian mixture to identify the average sensorimotor frequency distribution across trials, in comparison to the predicted EEG noise floor (see Blankertz et al., 2010 and Sannelli et al., 2019 for more information). Sensorimotor rhythm amplitudes over motor cortex during rest with eyes open are positively correlated to motor imagery BCI performance for both neurotypical individuals (Blankertz et al., 2010; Sannelli et al., 2019), and those with ALS (Geronimo, et al., 2016). Therefore, when the sensorimotor rhythm is present, increased amplitudes over left and right motor areas are expected to positively correlate to BCI performance. Additionally, Shu et al., (2018) found that individuals with neuromotor disorders who had smaller (more negative or closer to zero relative to baseline) sensorimotor rhythm values over both left and right hemisphere sensorimotor electrodes *during* motor imagery performance were more efficient at BCI switch control. Therefore, while here are no established reference values for ERS and ERD amplitudes, sensorimotor amplitudes during rest and motor imagery were evaluated both prior to the session to 1) ensure presence of the rhythms necessary for BCI control, and 2) evaluate an individual's unique neurophysiological profile prior to motor imagery BCI training. However, as BCI feedback may lead to enlargement of motor areas and sensorimotor modulations due to processes associated with neuroplasticity (Sannelli et al., 2019) these neurophysiological measures were additionally be evaluated during each training session.

2.4.3 Recurring number scale measures of participant perspectives and satisfaction

Along with neurophysiological assessment measures described above, number scale-based evaluations of participant characteristics were taken prior to and following each BCI training session to track changes associated with BCI learning.

2.4.3.1 Pre-session number scale measures (see appendix A).

1) **Fatigue, Motivation and Food Intake:** As motivation and fatigue may influence cognitive status and BCI performance (e.g., Nijboer et al., 2010; Kasahara et al., 2012), prior to each training session participant fatigue and motivation for BCI use were recorded via number scale with rating of 1 indicating 'normal fatigue' and 'unmotivated' to 9, 'extremely fatigued' and 'extremely motivated'. Furthermore, time since an individual's last meal was tracked as individuals with ALS may present with swallowing difficulties, which may decrease food intake and lower energy levels.

2.4.3.2 Post-session number scale measures (see appendix B).

1) **Fatigue**: To ascertain the level of fatigue associated with BCI control, a number scale rating was taken pre-and post to BCI control using the scale of 1 indicating 'normal fatigue', through 9 'extremely fatigued'. Overall fatigue associated with BCI use was calculated by subtracting their post session fatigue rating from pre-session fatigue rating.
2) **Device Satisfaction**: Levels of satisfaction with the BCI device were evaluated via a number scale of 1 indicating very unsatisfied, through 9 very satisfied.
3) **Frustration**: Levels of frustration with the BCI control were evaluated via a number scale of 1 indicating very low, through 9 very high.

4) **Physical and mental effort**: Levels of physical and mental effort associated with the BCI control were evaluated via a number scale of 1 indicating very low, through 9 very high.
5) **Overall levels of effort:** Overall level of effort (i.e., 'how hard' they had to work), were evaluated via a number scale of 1 indicating BCI control was very easy, through 9 very hard.

Chapter IV: Results

To facilitate understanding of findings, significant and relevant findings are ***bolded and underlined*** *throughout all reults sections.*

4.1 Initial BCI assessment measures for individuals with ALS

4.1.1 Cognition

Scores for each participant are provided in table 2 for the ALS-CBS and table 3 for the cognitive portion of the BCI screener. For the ALS-CBS, a total score of <17 indicates a concern for cognitive impairment. Differences in scores between participants were noted for sections including attention, with scores of 3, 3, 5 and 5 for participants A1, A4, A2 and A3 respectively, concentration with scores of 4, 5, 5 and 5 for participants A1, A2, A3 and A4 respectively, tracking and monitoring with scores of 4, 5, 5 and 5 for participants A2, A1, A3 and A4 respectively, initiation and retrieval with scores of 1, 3, 4 and 5 for participants A4, A1, A3 and A2 respectively, and total ALS-CBS score with scores of 14, 15, 19 and 19 for participants A4, A1, A2, A3. These total ALS-CBS scores indicate a concern of cognitive impairment for both participants A1 and A4.

For the cognitive portion of the BCI screener, differences in scores between participants were noted for sections including attention/working memory, with scores of 5, 5, 6 and 6 for participants A1, A2, A3 and A4 respectively, concentration with scores of 4, 5, 5 and 5 for participants A1, A2, A3 and A4 respectively, cognitive motor learning/abstract problem solving with sores of 4, 5, 5 and 5 for participants A1, A2, A3 and A4 respectively, and total cognitive score with scores of 22, 22, 24 and 24 for participants A1, A2, A3 and A4 respectively.

Table 2. Total and subsection scores for the ALS-CBS with a total score of <17 (bolded) indicating a concern for cognitive impairment. Maximum scores for each area are provided in parenthesis. Highest and lowest scores for each section are marked by a + and – respectively.

Participant	**Attention (/5)**	**Concentration (/5)**	**Tracking/monitoring (/5)**	**Initiation/retrieval (/5)**	**Total (/20)**
A1	3^-	4^-	5^+	3	**15**
A2	5^+	5^+	4^-	5^+	19^+
A3	5^+	5^+	5^+	4	19^+
A4	3^-	5^+	5^+	1^-	**14^-**

Table 3. Total and subsection scores for the cognitive portion of the BCI screener, with decreasing scores indicting an increased concern for the presence of BCI related skills. Maximum scores for each area are provided in parenthesis. Highest and lowest scores for each section are marked by a + and – respectively.

Participant	**Comprehension/ Orientation (/6)**	**Following directions**	**Attention/working memory (/6)**	**Cognitive motor learning/ abstract**	**Total Score**

		(/6)		problem solving (/6)	(/24)
A1	6	6	5^{-}	5^{-}	**$\underline{22^{-}}$**
A2	6	6	5^{-}	5^{-}	**$\underline{22^{-}}$**
A3	6	6	6^{+}	6^{+}	24^{+}
A4	6	6	6^{+}	6^{+}	24^{+}

4.1.2 (Motor) imagery

Scores for each participant are provided in table 4 for the motor imagery portion of the BCI screener. Differences in scores between participants were noted for sections including self-ratings of first-person motor imagery with scores of 2, 3.2, 3.4 and 3.6 for participants A4, A1, A3 and A2 respectively. First person imagery ratings were averaged across imagined upper and lower limb actions per the procedures of Pitt & Brumberg (2018b) due to limited score variability between individual tasks, hand rotation scores were 3, 4, 5 and shape rotation scores were 2, 4, 4 and 5 for participants A3, A1, A2 and A4 respectively.

Table 4. Participant scores for the motor imagery and visuospatial portions of the BCI screener. with decreasing scores indicting an increased concern for the presence of BCI related skills. Maximum scores for each area are provided in parenthesis. Highest and lowest scores for each section are marked by a + and – respectively.

Participant	**Average self-rating of first-person limb imagery (/5)**	**Hand rotation (/5)**	**Object rotation (/5)**	**Shape rotation (/5)**

A1	3.2	3^{-}	5	4
A2	3.6^{+}	5^{+}	5	4
A3	3.4	4	5	2^{-}
A4	2^{-}	5^{+}	5	5^{+}

4.1.3 Functional motor control and manual ability

Motor assessment guided by the BCI screener revealed participant A1 was ambulatory with no impairments noted in the upper or lower limbs. For the upper limb, participant A2 had limited range of motion, weakness, and decreased ability to grasp/grip, with increased impairment on increased on his right side. For the lower limb, participant A2 was ambulatory with a walker, with decreased range of motion and increased leg spasticity when standing. Participant A3 had a severe upper limb impairment with physical abilities limited to movement of her right index finger on left hand, and limited ability to grip with the right hand. For the lower limb participant 3 was not ambulatory, retaining the ability to lift her thighs and move her toes. For the upper limb, participant A4 had limited range of motion, weakness, and decreased ability to grasp/grip bilaterally. Fine motor impairments were decreased for his left side. For the lower limb, participant 4 reported minimal impairments and was ambulatory without assistance. He reported being told his legs were ‘still strong’ during recent assessment from physical therapy. No participants had difficulties with oculomotor control.

Scores for each participant are provided in table 5 for the ALS-FRS, MACS, and BFMF. Differences between participants were noted for the ALS-FRS, for which lower scores indicate greater motor impairment, with scores of 15, 26, 33, and 34 for participants A3, A4, A1 and A2 respectively. In contrast to the ALS-FRS, higher scores for the MACS and BFMF indicate

greater motor impairment. Scores for the MACs included 1, 2, 2, and 5 for participants A1, A2, A4, and A3 respectively. For the BFMF scores included 1, 2, 3, and 5 for participants A1, A2, A4, and A3 respectively.

Table 5. Participant results for motor control and manual ability. Scores/descriptions noting increased motor impairments are marked by a -, and lowest motor impairment by a +. Maximum scores are noted in parenthesis, as applicable. Note: For the ALS- Functional Rating Scale (ALS-FRS), higher scores mean decreased motor impairment. However, for the Manual ability classification systems (MACS) and Bimanual fine motor function classification system (BFMF) lower scores indicate decreased motor impairment. Abbreviations ROM = range of motion

Participant	**ALS-FRS (/40)**	**MACS (/5)**	**BFMF (/5)**	**BCI screener: upper limb**	**BCI screener: lower limb**
A1	33	1^{+}	1^{+}	No impairment $^{+}$	**No impairment** $^{+}$
A2	34^{+}	2	2	Limited ROM. Decreased fine motor control and ability to grasp/grip	Limited ROM and weakness Ambulatory with assistance Limb spasticity
A3	15^{-}	5^{-}	5^{-}	Highly limited finger movement and ability to grasp $^{-}$	**Non-ambulatory** **Minimal movement of legs and thighs** $^{-}$
A4	26	2	3	Limited ROM. Decreased fine motor control and ability to grasp/grip	**Ambulatory without assistance.** **Participant reported legs as 'still strong'** $^{+}$

4.1.4 Initial Neurophysiological measures

Full neurophysiological measures for each participant prior to BCI use are provided in table 6 including event related synchronization (ERS) peak amplitude, ERS peak amplitude minus the estimated noise level, and the ERS peak amplitude minus peak event related desynchronization amplitude (ERS-ERD difference) for the frequency band of 6-13 Hz. For all participants measures were calculated from electrode locations C3 for right hand movement, and C4 for left hand movement. Furthermore, as beginning in session 2, participant A4 utilized lower limb movement for BCI control. Therefore, his initial neurophysiological measures are also provided for electrode locations C1 and C2, which better represent lower limb motor control locations. Participant A1 presented with the highest peak ERS amplitude of 0.726 microvolts^2, peak ERS amplitude minus noise levels of 0.531 microvolts^2, and ERS-ERD difference of 0.254 microvolts^2. The lowest measure of peak ERS amplitude was .048 microvolts^2, for A3, peak ERS amplitude minus noise levels was 0.003 microvolts^2 for A4 at electrode C1, and ERS-ERD difference of -0.076 microvolts^2 for P3.

Table 6. Neurophysiological assessment measures for each participant. The largest measurements of event related synchronization (ERS) amplitude, and the largest difference between ERS event related desynchronization (ERD) amplitudes are marked by a +. Lowest measures are marked my a -. Units are in microvolts^2

Participant	**Task**	**Peak amplitude ERS (rest)**	**Noise amplitude at peak ERS**	**ERS – noise**	**Peak amplitude ERD**	**Peak ERS – Peak ERD**
A1	Right hand	**0.726$^+$**	0.195	**0.531$^+$**	0.472	**.254$^+$**

A1	Left hand	0.596	0.123	0.473	0.606	-0.01
A2	Right hand	0.095	0.034	0.061	0.084	0.011
A2	Left hand	0.105	0.036	0.069	0.113	-0.008
A3	Right hand	**0.048**-	0.009	0.039	0.052	**-0.004**
A3	Left hand	0.144	0.017	0.127	0.22	-0.076-
A4	Right hand	0.056	0.015	0.041	0.063	-0.007
A4	Left hand	0.053	0.021	0.033	0.057	-0.004
A4	Right knee	0.103	0.1	**0.003**-	0.166	-0.063
A4	Left knee	0.17	0.139	0.031	0.128	0.042

4.2 BCI Learning Trajectories

BCI accuracy was calculated via Cohen's Kappa, which represents the overall agreement between the BCI decoded output, and what the user intended for both select, and 'keep scanning' trials. Cohen's Kappa values have been previously used to assess BCI outcomes (e.g., Daly et al., 2013; Zhang, Jadavji, Zewdie & Kirton, 2019), with a Cohen's Kappa value of 0 to 0.20 indicates no to slight agreement between the BCI output and user intention, 0.21 to 0.4 as fair agreement, 0.41 to 0.6 as moderate agreement, 0.61 to 0.8 as substantial agreement and .81 to 1 as almost perfect agreement (e.g., McHugh, 2012). Negative kappa values indicate performance below chance levels. For the row-column scanning paradigm, Cohen's Kappa is suitable for

outcome assessment as it adjusts for bias in trial/condition numbers, representing relative increases and decreases in true negative (correct non-selects) and positive rates (correct selects), and false negative (the BCI incorrectly does not select an item) and false positive (the BCI incorrectly selects an item) rates. This is important as during row-column scanning multiple no-selection/continue scanning trials are required to scan through the non-target letters and complete a target selection task. Therefore, traditional measures of percent accuracy (number of correct selects and non-selects/total trials) are weighted toward performance of non-selection tasks in this BCI paradigm, skewing this performance metric. Furthermore, other measures such as number of letters selected only show improved skill learning in the area of making item selections (true positive rates). However, learning BCI control in regard to true negative rates, which allows the interface to keep scanning until the target letter is highlighted, is an important factor in gaining row-column scanning BCI control. Similar to true positive rates, improving true negative rates requires skill learning to produce the targeted brain rhythm (i.e., the ERS; e.g., Friedrich et al., 2009). Therefore, performance metrics such a Cohen s Kappa that account for changes in both true positive and negative performance, are ideal for reflecting skill learning in this BCI paradigm.

4.2.1 Neurotypical Learning Trajectories

For neurotypical participant T1, their average BCI accuracy across three sessions was 0.412 (range: 0.3825–0.4465; *SD* = .032), reaching levels of moderate agreement. Her overall increase in BCI accuracy (highest performance minus lowest performance) was 0.064. Cohens Kappa values and 95% confidence intervals for each session are provided in table 7, and figure 2.

Table 7. Cohens Kappa values and 95% confidence intervals (CI) for each of the three BCI training sessions for neurotypical participant T1.

Session Number	Cohens Kappa	95% CI upper bound	95% CI lower bound
1	0.3825	0.4994	0.2757
2	0.4465	0.5661	0.3268
3	0.406	0.5079	0.304

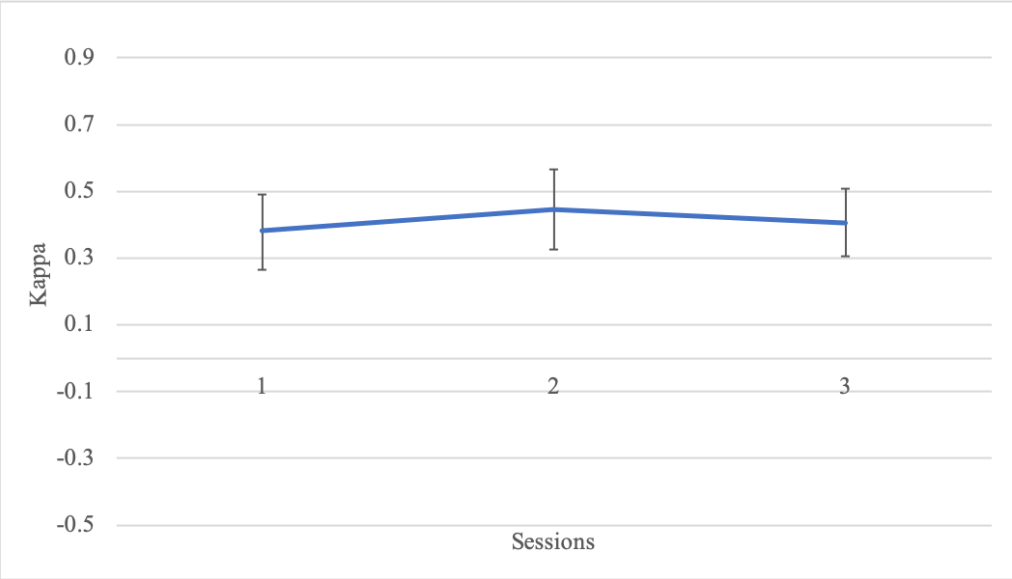

Figure 2. The BCI learning trajectory across 3 sessions for T1

For neurotypical participant T2, their average BCI accuracy across three sessions was 0.689 (range: 0.6574–0.7339; *SD* = .04), reaching substantial agreement levels, though the 95% confidence interval ranges extend into the range of substantial to almost perfect agreement for session 3. His overall increase in BCI accuracy (highest performance minus lowest performance) was 0.099. Cohens Kappa values and 95% confidence intervals for each session are provided in table 8, and figure 3.

Table 8. Cohens Kappa values and 95% confidence intervals (CI) for each of the three BCI training sessions for neurotypical participant T2.

Session Number	**Cohens Kappa**	**95% CI upper bound**	**95% CI lower bound**
1	0.6751	0.7932	0.5571
2	0.6574	0.7637	0.5511
3	0.7339	0.8141	0.6537

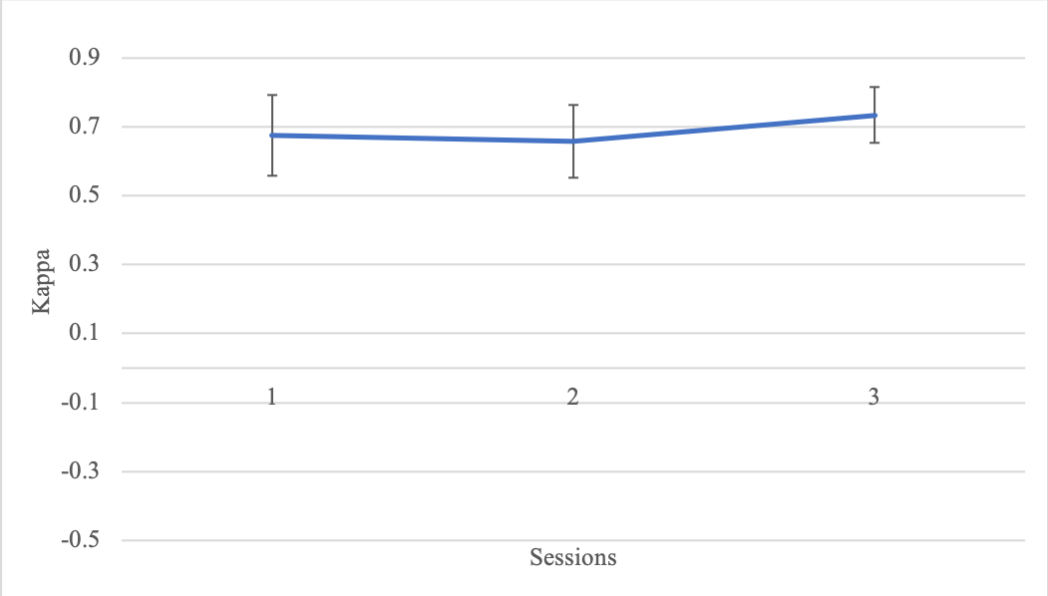

Figure 3 The BCI learning trajectory across 3 sessions for T2

For neurotypical participant T3, their average BCI accuracy across three sessions was 0.387 (range: 0.0615–0.568; *SD* = .283), reaching the upper levels of moderate agreement, though the 95% confidence interval range extends into the range of substantial agreement for sessions 2 and 3. Her overall increase in BCI accuracy (highest performance minus lowest performance) was 0.506, showing a large increase in BCI learning between sessions 1 and 2.

Cohens Kappa values and 95% confidence intervals for each session are provided in table 9, and figure 4.

Table 9. Cohens Kappa values and 95% confidence intervals (CI) for each of the three BCI training sessions for neurotypical participant T3.

Session Number	**Cohens Kappa**	**95% CI upper bound**	**95% CI lower bound**
1	0.0615	0.2008	-0.0778
2	0.5679	0.688	0.4478
3	0.532	0.6485	0.4155

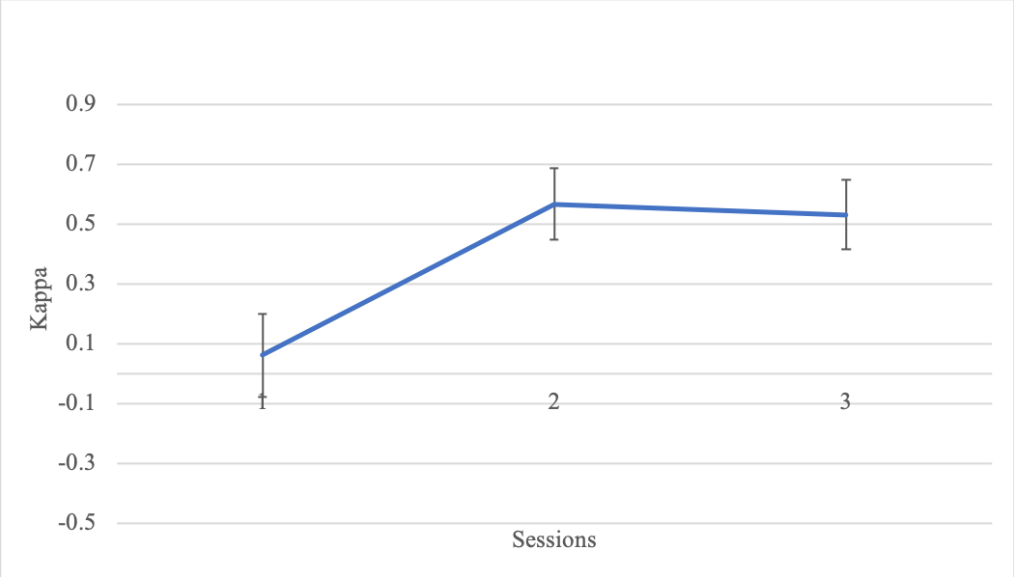

Figure 4. The BCI learning trajectory across 3 sessions for T3

4.3 Learning Trajectories of those with ALS

4.3.1 Participant A1: BCI Learning Trajectory

For participant A1, their average BCI accuracy across all twelve sessions was 0.333 (range: 0.020–0.544; *SD* = .151) reaching moderate levels of agreement, though the 95% confidence interval range extends into the range of substantial agreement for sessions 6 and 7. Their overall increase in BCI accuracy (highest performance minus lowest performance) was 0.524. Cohens Kappa values and 95% confidence intervals for each session are provided in table 10. The learning trajectory of participant A1 is provided in figure 5, with their learning trajectory associated with a slope of 0.0023 but showing a large increase in BCI learning between sessions 1 and 2.

Table 10. Cohens Kappa values and 95% confidence intervals (CI) for each BCI training session for participant A1.

Session Number	Cohens Kappa	95% CI upper bound	95% CI lower bound
1	0.020	0.122	-0.082
2	0.445	0.582	0.308
3	0.423	0.552	0.293
4	0.377	0.520	0.235
5	0.289	0.407	0.171
6	0.522	0.641	0.403
7	0.544	0.654	0.431
8	0.223	0.325	0.122
9	0.195	0.286	0.104

10	0.243	0.354	0.132
11	0.285	0.397	0.174
12	0.425	0.560	0.290

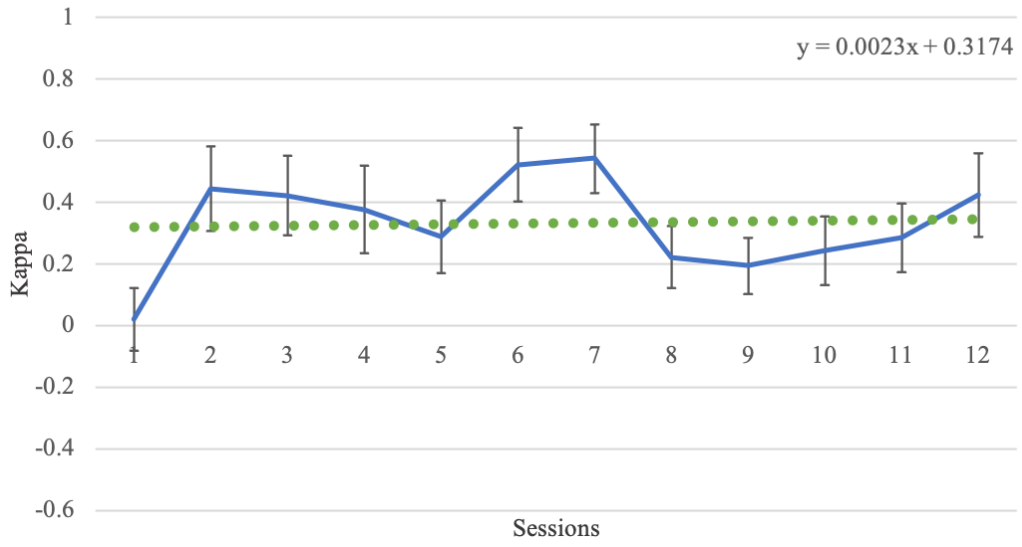

Figure 5. The BCI learning trajectory across 12 sessions for participant A1. The linear trend line is shown in green along with the corresponding equation.

4.3.2 Participant A1: Recurring Measures in relation to BCI performance

Within subject correlations between recurring number scale and neurophysiological recurring measures and BCI accuracy (Cohens Kappa) were assessed using a within subject Spearman's rank order correlation using the 12 data points collected from each BCI training session. For clarity, data points for each recurrent measure across the twelve sessions for each participant are provided in appendix C.

Results indicate that 1) **motivation** ratings, taken at the start of each training session, did not vary for participant 1 with a score of 9 (extremely motivated) prior to beginning each session, 2) **fatigue** ratings, taken prior to the start of each training session, had an average rating of 3.75 (*SD* = 1.66), ranging from 1 (normal) to 6 (moderate-high), and a non-significant correlation ($r_s(10)$ = -.389 *p* = .212) with BCI accuracy (range: 0.020–0.544; *M* = 0.333; *SD* = .151), 3) **time since last meal**, taken at the start of each training session, averaged 0.958 hours (range 0–3; *SD* = 1.25), and a non-significant correlation ($r_s(10)$ = .0, *p* = 1) with BCI accuracy, 4) **BCI satisfaction ratings, taken at the end of each training session, had an average rating of 7.33 (*SD* = .985), ranging from 5 (neutral) to 9 (very satisfied), and a significant positive correlation ($r_s(10)$ = .651, *p* <.05) with BCI accuracy,** 5) **frustration with device control** ratings taken at the end of each training session, had an average rating of 3.25 (*SD* = 1.36), ranging from 1 (very low) to 5 (neutral), and demonstrated a non-significant correlation ($r_s(10)$ = .05, *p* = .877 with BCI accuracy, 6) **mental effort ratings** taken at the end of each training session, had an average rating of 6.17 (*SD* = 1.34), ranging from 3 (fairly low) to 8 (fairly-very high), and a non-significant correlation **($r_s(10)$ = -.479, *p* = .115)** with BCI accuracy, 7) **physical effort** ratings taken at the end of each training session, had an average rating of 1.42 (*SD* = 0.669), ranging from 1 (very low) to 3 (fairly low), and a non-significant correlation ($r_s(10)$ = -.08, *p* = .795) with BCI accuracy, 8**) overall 'hardness'** ratings taken at the end of each training session, had an average rating of 4.58 (*SD* = 1.73), ranging from 2 (very-fairly easy) to 8 (fairly-very hard), and a non-significant correlation ($r_s(10)$ = -.011, *p* = .974) with BCI accuracy.

For the neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3 had an average value of 0.355 microvolts² (range: 0.16–0.8; *SD* = 0.211), and a non-significant correlation ($r_s(10)$ = -.266, *p* = .404) with BCI accuracy. C4 had an average

value of 0.476 microvolts² (range: 0.18–1.08; *SD* = 0.299), and a non-significant correlation ($r_s(10) = -.210$, $p = .513$) with BCI accuracy, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 had an average value of 0.182 microvolts² (range: 0–0.53; *SD* = 0.164), and a non-significant correlation ($r_s(10) = -.245$, $p = .443$) with BCI accuracy. C4 had an average value of 0.288 microvolts² (range: 0.4–0.84; *SD* = 0.238), and a non-significant correlation ($r_s(10) = .007$, $p = .983$) with BCI accuracy, **3) the ERS-ERD difference for C3 had an average value of 0.076 microvolts² (range: -0.09–0.25; *SD* = 0.086), and a non-significant correlation ($r_s(10) = -.241$, $p = .505$) with BCI accuracy. C4 had an average value of 0.135 microvolts² (range: -0.01–0.54; *SD* = 0.165), and a non-significant correlation ($r_s(10) = .490$, $p = .106$) with BCI accuracy.**

4.3.3 Participant A1: Recurring Measures in relation to session number

Within subject correlations between number scale and neurophysiological measures and session number were evaluated via a Spearman's rank order correlation using the 12 data points collected during each BCI training session.

1) **within-session fatigue** (ratings taken at the *start* of each training session minus ratings taken at the *end* of the session), **had a an average rating of -1.08 (*SD* = 1.31),** ranging from -4 (rating moderate-high levels of fatigue prior to BCI use and normal-mild following BCI training) to 1 (normal prior to BCI use and normal-mild following BCI training) and a non-significant correlation ($r_s(10) = .124$, $p = .423$) with session number, 2) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.1$, $p = .757$) with session number, 3) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.434$, $p = .157$) with session number, 4) **physical effort** ratings taken at the end of each training session demonstrated a non-

significant correlation ($r_s(10) = .050$, p = .876) with session number, 5) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.043$, $p = .895$) with session number.

For neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3 demonstrated a non-significant correlation ($r_s(10) = -.273$, $p = .391$ with session number. C4 demonstrated a non-significant correlation ($r_s(10) = -.364$, $p = .245$) with session number, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 demonstrated a non-significant correlation ($r_s(10) = -.517$, $p = .085$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = -.294$, $p = .354$) with session number, 3) the **ERS-ERD difference** for C3, demonstrated a non-significant correlation ($r_s(10) = -.378$, $p = .225$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = .007$, $p = .983$) with session number.

4.3.4 Participant A1: Recurring measures in relation to satisfaction ratings

Within subject correlations between number scale measures and satisfaction were evaluated via a Spearman's rank order correlation using the 12 data points collected during each BCI training session. Regarding ratings correlations to an individual's perception of BCI satisfaction: 1) **within-session fatigue** demonstrated a non-significant correlation ($r_s(10) = .382$, $p = .221$) with BCI satisfaction ratings, 2) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.109$, $p = .736$) with BCI satisfaction ratings, 3) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.359$, $p = .252$) with BCI satisfaction ratings, 4) **physical effort** ratings taken at the end of each training demonstrated a non-significant correlation ($r_s(10) = -.429$, $p = .153$) with BCI satisfaction ratings, 5) **Overall**

'hardness' ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .124$, $p = .703$) with BCI satisfaction ratings.

4.4.1 Participant A2: BCI Learning Trajectory

For participant A2, their average BCI accuracy across all twelve sessions was 0.139 (range: -.051 –0.340; *SD* = .117) indicating slight agreement, and while **overall his BCI performance was highly variable**, the 95% confidence interval range extends into the range of moderate agreement for sessions 1 and 4. Their overall increase in BCI accuracy (highest performance minus lowest performance) was 0.340. Cohens Kappa values and 95% confidence intervals for each session are provided in table 11. The learning trajectory for participant A2 is provided in figure 6, with their learning trajectory associated with a slope of 0.0033.

Table 11. Cohens Kappa values and 95% confidence intervals (CI) for each BCI training session for participant A2.

Session Number	Cohens Kappa	95% CI upper bound	95% CI lower bound
1	0	0.438	-0.438
2	0.17	0.283	0.059
3	-0.051	0.069	-0.171
4	0.340	0.551	0.249
5	0.221	0.346	0.096
6	0.087	0.197	-0.024
7	0.134	0.241	0.026
8	0.222	0.355	0.089
9	0.046	0.173	-0.080

10	0.179	0.331	0.027
11	0.126	0.249	0.003
12	0.131	0.241	0.021

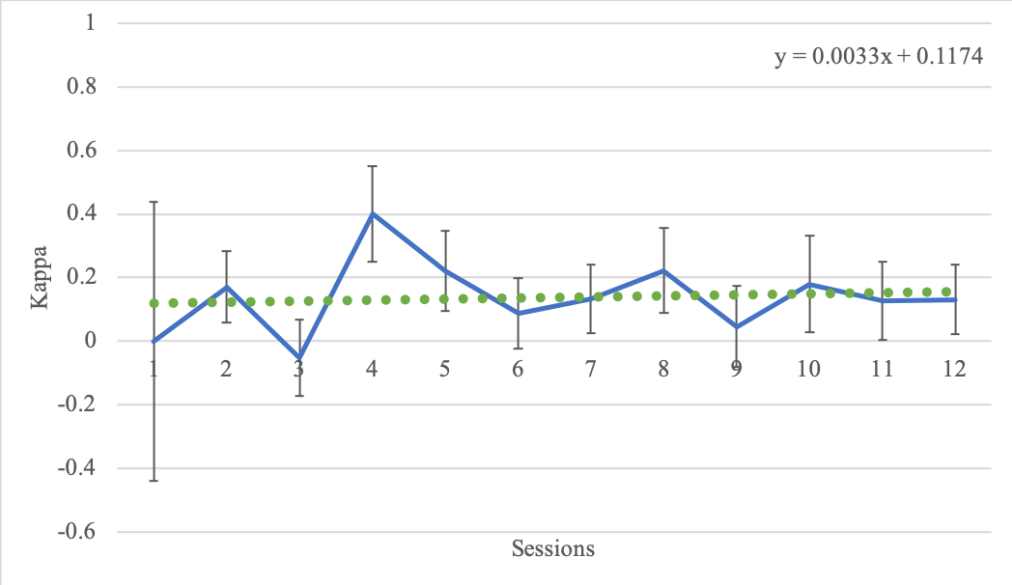

Figure 6. The BCI learning trajectory across 12 sessions for A2. The linear trend line is shown in green along with the corresponding equation.

4.4.2 Participant A2: Recurring Measures in relation to BCI performance

Results indicate that for 1) **motivation** ratings, had an average rating of 7.33 (*SD* = .888), ranging from 6 (moderate-high) to 9 (extremely motivated) and a non-significant correlation ($r_s(10)$ = -.000 p = 1) with BCI accuracy (range: -0.051–0.340; *M* = 0.139; *SD* = 0.117), 2) **fatigue** ratings, taken prior to the start of each training session, had an average rating of 2.67 (*SD* = 1.56), ranging from 1 (normal) to 5 (moderate), and a non-significant correlation ($r_s(10)$ = -.495 p = .102) with BCI accuracy, 3) **time since last meal**, taken at the start of each training session, **averaged 9.72 hours** (range 0.41–16; *SD* = 6.77), and a non-significant correlation

($r_s(10) = -.331$, $p = .293$) with BCI accuracy, 4) **BCI satisfaction ratings**, taken at the end of each training session, had an average rating of 6.75 (*SD* = 1.82), ranging from 4 (mildly unsatisfied-neutral) to 9 (very satisfied), and a non-significant correlation ($r_s(10) = .364$, $p = .245$) with BCI accuracy, 5) **frustration with device control** ratings taken at the end of each training session, had an average rating of 5.25 (*SD* = 1.76), ranging from 2 (low-fairly low) to 8 (fairly-very high), and a non-significant correlation ($r_s(10) = -.240$, $p = .452$ with BCI accuracy, 6) **mental effort ratings** taken at the end of each training session, had an average rating of 6.92 (*SD* = 1.16), ranging from 4 (fairly low-neutral) to 8 (fairly-very high), and a non-significant correlation **($r_s(10) = -.478$, $p = .116$)** with BCI accuracy, 7) **physical effort** ratings taken at the end of each training session, had an average rating of 4.25 (*SD* = 1.42), ranging from 2 (very-fairly low) to 6 (neutral-fairly high), and a non-significant correlation ($r_s(10) = -.3$, $p = .344$) with BCI accuracy, 8**) overall 'hardness'** ratings taken at the end of each training session, had an average rating of 6.17 (*SD* = 1.34), ranging from 4 (fairly easy-neutral) to 7 (fairly hard), and a non-significant correlation ($r_s(10) = -.202$, $p = .530$) with BCI accuracy.

For the neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3 had an average value of 0.187 microvolts² (range: 0.03–0.5; *SD* = 0.156), and a non-significant correlation ($r_s(10) = .413$, $p = .183$) with BCI accuracy. **C4 had an average value of 0.276 microvolts² (range: 0.03–0.61; *SD* = 0.213), and a significant positive correlation ($r_s(10) = .622$, $p = .031$) with BCI accuracy**, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 had an average value of 0.114 microvolts² (range: 0.02–0.4; *SD* = 0.119), and a non-significant correlation ($r_s(10) = .228$, $p = .447$) with BCI accuracy. C4 had an average value of 0.184 microvolts² (range: 0.02–0.52; *SD* = 0.183), and a non-significant correlation ($r_s(10) = .371$, $p = .236$) with BCI accuracy, 3) the

ERS-ERD difference for C3 had an average value of 0.003 microvolts² (range: -0.23–0.13; *SD* = 0.088), and a non-significant correlation ($r_s(10) = .490$, $p = .106$) with BCI accuracy. C4 had an average value of 0.006 microvolts² (range: -.023–0.14; *SD* = 0.098), and a non-significant correlation ($r_s(10) = -0.049$ $p = .880$) with BCI accuracy.

4.4.3 Participant A2: Recurring Measures in relation to session number

1) **Motivation ratings, taken prior to the start of each training session demonstrated a significant negative correlation ($r_s(10) = -.763$, $p < .05$) with session number**, 2) **within-session fatigue** (**range: -2–2; *M* = 0.417** , *SD* = 1.31) demonstrated a non-significant correlation ($r_s(10) = .131$, $p = -.462$) with session number, 3) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.1$, $p = .757$) with session number, 4) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.359$, $p = .252$) with session number, 5) **physical effort** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .662$, p = .141) with session number, 6) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.168$, $p = .602$) with session number. For neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3, demonstrated a non-significant correlation ($r_s(10) = -.259$, $p = 471$ with session number. C4 demonstrated a non-significant correlation ($r_s(10) = -.049$, $p = .880$) with session number, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 demonstrated a non-significant correlation ($r_s(10) = -.060$, $p = .854$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = .301$, $p = .342$) with session number, 3) the **ERS-ERD difference** for C3 demonstrated a non-

significant correlation ($r_s(10) = -.077$, $p = .812$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = .399$, $p = .199$) with session number.

4.4.4 Participant A2: Recurring measures in relation to satisfaction ratings

1) **within-session fatigue** demonstrated a non-significant correlation ($r_s(10) = -.175$, $p = .586$) with BCI satisfaction ratings, 2) **frustration with device control** ratings taken at the end of each training session demonstrated a significant negative correlation ($r_s(10) = -.841$, $p < .05$) with BCI satisfaction ratings, 3) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.125$, $p = .7$) with BCI satisfaction ratings, 4) **physical effort** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.337$, $p = .284$) with BCI satisfaction ratings, 5) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .231$, $p = .469$) with BCI satisfaction ratings.

4.5.1 Participant A3: BCI Learning Trajectory

For participant A3, her average BCI accuracy across all twelve sessions was -0.01 (range: -.017 –0.13; *SD* = .096) indicating below chance levels to no-slight agreement. Her overall increase in BCI accuracy (highest performance minus lowest performance) was 0.147. Cohens Kappa values and 95% confidence intervals for each session are provided in table 12. The learning trajectory for participant A3 is provided in figure 7. While variable, her **learning trajectory began at session approximately session 3 and is associated with a slope of 0.0155.** However, the **correlation between session number and BCI performance approached but did not reach significance ($r_s(10) = .517$, $p = .085$).**

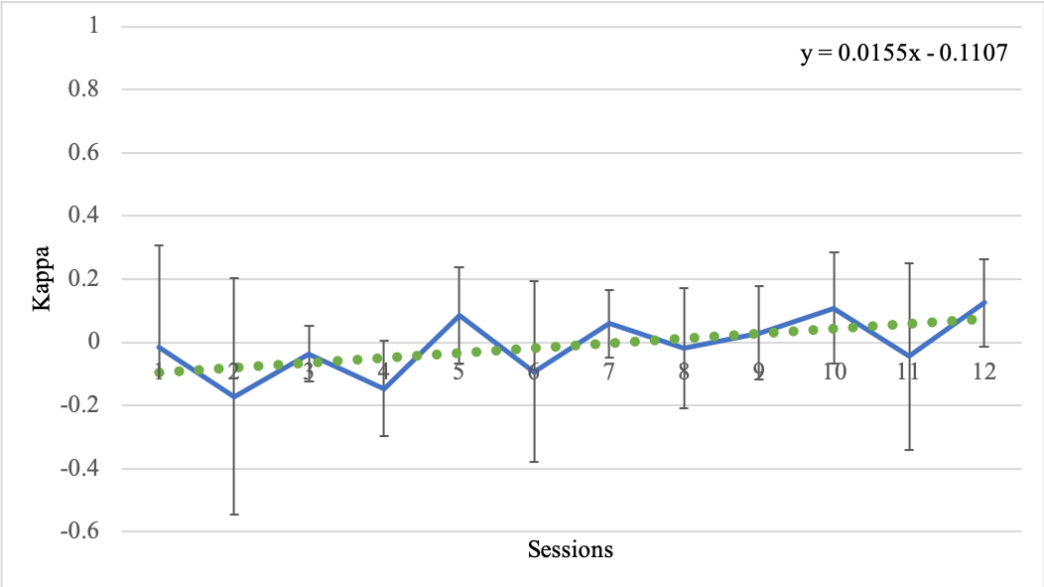

Figure 7. The BCI learning trajectory across 12 sessions for A3. The linear trend line is shown in green along with the corresponding equation.

Table 12. Cohens Kappa values and 95% confidence intervals (CI) for each BCI training session for participant A3.

Session Number	**Cohens Kappa**	**95% CI upper bound**	**95% CI lower bound**
1	-0.016	0.306	-0.339
2	-0.172	0.203	-0.546
3	-0.036	0.051	-0.125
4	-0.146	0.005	-0.297
5	0.085	0.237	-0.068
6	-0.092	0.194	-0.378
7	0.059	0.167	-0.049

8	-0.018	0.173	-0.21
9	0.0289	0.1767	-0.1188
10	0.1079	0.2843	-0.0685
11	-0.0446	0.2508	-0.34
12	0.1256	0.2643	-0.013

4.5.2 Participant A3: Recurring Measures in relation to BCI performance

Results indicate that for 1) **motivation** ratings, had an average rating of 8.58 (*SD* = .515), ranging from 8 (fairly-extremely motivated) to 9 (extremely motivated) and a non-significant correlation ($r_s(10) = -.416$, $p = .178$) with BCI accuracy (range: -0.17–0.13; *M* = -.01; *SD* = 0.096), 2) **fatigue** ratings, taken prior to the start of each training session, had an average rating of 3.88 (*SD* = 1.63), ranging from 1 (normal) to 7.5 (high), and a non-significant correlation ($r_s(10) = .288$ $p = .365$) with BCI accuracy, 3) **time since last meal**, taken at the start of each training session, averaged 2.16 hours (range 0.33–3; *SD* = 1.06), and a non-significant correlation ($r_s(10) = .287$, $p = .365$) with BCI accuracy, 4) **BCI satisfaction ratings, taken at the end of each training session, had an average rating of 5.08 (*SD* = 1.73), ranging from 2 (very-mildly unsatisfied) to 7 (mildly satisfied), and a significant positive correlation ($r_s(10) = .715$, $p < .05$) with BCI accuracy**, 5) **frustration with device control** ratings taken at the end of each training session, had an average rating of 6.08 (*SD* = 1.16), ranging from 4 (fairly low-neutral) to 8 (fairly-very high), and a non-significant correlation ($r_s(10) = -.235$, $p = .463$ with BCI accuracy, 6) **mental effort ratings** taken at the end of each training session, had an average rating of 7 (*SD* = 1.35), ranging from 5 (neutral) to 9 (very high), and a non-significant correlation **($r_s(10) = -.271$, $p = .394$)** with BCI accuracy, 7) **physical effort** ratings taken at the

end of each training session, had an average rating of 5.08 (*SD* = 1.68), ranging from 1 (very low) to 7 (fairly high), and a non-significant correlation ($r_s(10) = .101$, $p = .734$) with BCI accuracy, 8**) overall 'hardness'** ratings taken at the end of each training session, had an average rating of 6.5 (*SD* = 1.24), ranging from 4 (fairly easy-neutral) to 9 (very hard), and a non-significant correlation ($r_s(10) = -.143$, $p = .658$) with BCI accuracy.

For the neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3 **had an average value of 0.520 microvolts²** (range: 0.05–1.89; *SD* = 0.583), and demonstrated a non-significant correlation ($r_s(10) = -.140$, $p = .665$) with BCI accuracy. C4 had an average value of 0.55 microvolts² (range: 0.07–1.54; *SD* = 0.558), and demonstrated a non-significant correlation ($r_s(10) = -.133$, $p = .681$) with BCI accuracy, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 had an average value of 0.357 microvolts² (range: 0.03–0.96; *SD* = 0.379), and demonstrated a non-significant correlation ($r_s(10) = -.161$, $p = .618$) with BCI accuracy. C4 had an average value of 0.371 microvolts² (range: 0.4–1.01; *SD* = 0.372), and demonstrated a non-significant correlation ($r_s(10) = -.070$, $p = .829$) with BCI accuracy, 3) the **ERS-ERD difference** for C3 had an average value of -0.023 microvolts² (range: -0.18–0.50; *SD* = 0.170), and demonstrated a non-significant correlation ($r_s(10) = -.127$, $p = .695$) with BCI accuracy. C4 had an average value of 0.001 microvolts² (range: -.08–0.12; *SD* = 0.055), and demonstrated a non-significant correlation ($r_s(10) = 0.406$, $p = .191$) with BCI accuracy.

4.5.3 Participant A3: Recurring Measures in relation to session number

1) **Motivation ratings, taken prior to the start of each training session demonstrated a significant negative correlation ($r_s(10) = -.857$, $p = <.001$) with session number**, 2) **within-session fatigue (range: -1–6; *M* = 1.29 , *SD* = 2.11)** demonstrated a non-significant correlation

($r_s(10) = .-.359$, $p = .252$) with session number, 3) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.087$, $p = .789$) with session number, 4) **metal effort ratings taken at the end of each training session demonstrated a significant negative correlation ($r_s(10) = -.699$, $p < .05$) with session number**, 5) **physical effort** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .242$, $p = .449$) with session number, 6) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.384$, $p = .218$) with session number. For neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C3, demonstrated a non-significant correlation ($r_s(10) = -.182$, $p = 572$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = -.399$, $p = .199$) with session number, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C3 demonstrated a non-significant correlation ($r_s(10) = -.287$, $p = .366$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = -.472$, $p = .167$) with session number, 3) the **ERS-ERD difference** for C3 demonstrated a non-significant correlation ($r_s(10) = .331$, $p = .293$) with session number. C4 demonstrated a non-significant correlation ($r_s(10) = .490$, $p = .106$) with session number.

4.5.4 Participant A3: Recurring measures in relation to satisfaction ratings

1) **within-session fatigue** demonstrated a non-significant correlation ($r_s(10) = -.392$, $p = .207$) with BCI satisfaction ratings, 2) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.450$, $p = .142$) with BCI satisfaction ratings, 3) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .237$, $p = .459$) with BCI satisfaction ratings, 4) **physical effort** ratings taken at the end of each training session demonstrated a non-

significant correlation ($r_s(10) = .050$, $p = .877$) with BCI satisfaction ratings, 5) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .124$, $p = .7$) with BCI satisfaction ratings.

4.6.1 Participant A4: BCI Learning Trajectory

For participant A4, their average BCI accuracy across all twelve sessions was .199 (range: -0.05–0.47; *SD* = .177) indicating slight agreement. However, kappa values and confidence intervals increased into the **upper levels of moderate agreement for sessions 10 and 11.** His overall increase in BCI accuracy (highest performance minus lowest performance) was 0.52. Cohens Kappa values and 95% confidence intervals for each session are provided in table 13. The learning trajectory for participant A4 is provided in figure 8, **with session number being significantly, positively, correlated to BCI performance ($r_s(10) = .699$, $p < .05$).** Their learning trajectory began at sessions 3 to 4 and is associated with a slope of 0.0347, which was the largest slope for all participants with ALS.

Table 13. Cohens Kappa values and 95% confidence intervals (CI) for each BCI training session for participant A4.

Session Number	Cohens Kappa	95% CI upper bound	95% CI lower bound
1	0	0.021	-0.021
2	-0.051	0.051	-0.152
3	-0.044	0.091	-0.179
4	0.158	0.333	-0.017
5	0.156	0.315	-0.002
6	0.253	0.356	0.151

7	0.373	0.488	0.258
8	0.278	0.409	0.146
9	0.312	0.409	0.215
10	0.407	0.511	0.302
11	0.468	0.591	0.345
12	0.078	0.213	-0.057

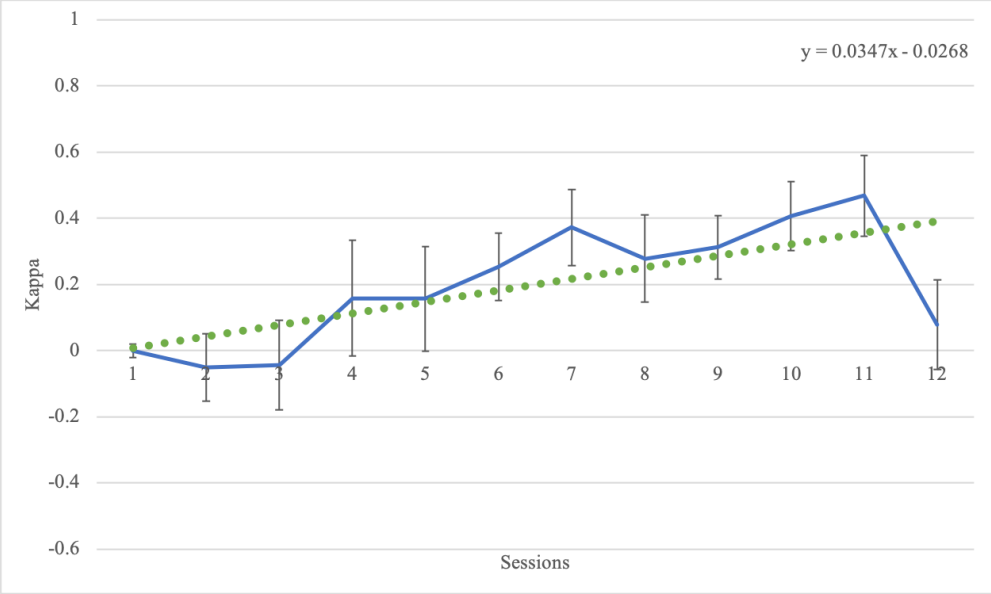

Figure 8. The BCI learning trajectory across 12 sessions for A4. The linear trend line is shown in green along with the corresponding equation.

4.6.2 Participant A4: Recurring Measures in relation to BCI performance

Results indicate that for 1) **motivation** ratings, had an average rating of 7.42 (*SD* = .792), ranging from 6 (moderate-high) to 8 (fairly-extremely motivated) and a non-significant correlation ($r_s(10) = -.158$, $p = .625$) with BCI accuracy (range: -0.05–0.47; *M* = .199; *SD* = 0.177), 2) **fatigue** ratings, taken prior to the start of each training session, had an average rating

of 5.49 (*SD* = 1.38), ranging from 2 (normal-mild) to 7 (high), and a non-significant correlation ($r_s(10) = .392$ $p = .208$) with BCI accuracy, 3) **time since last meal**, taken at the start of each training session, averaged 1.8 hours (range 1–3.5; *SD* = .634), and a non-significant correlation ($r_s(10) = .044$, $p = .892$) with BCI accuracy, 4) **BCI satisfaction ratings**, taken at the end of each training session, had an average rating of 7.25 (*SD* = .866), ranging from 6 (neutral-mildly unsatisfied) to 9 (very satisfied), and a non-significant correlation ($r_s(10) = .136$, $p = .674$) with BCI accuracy, 5) **frustration with device control** ratings taken at the end of each training session, had an average rating of 4.17 (*SD* = 1.85), ranging from 2 (low-fairly low) to 7 (fairly high), and a non-significant correlation ($r_s(10) = -.501$, $p = .097$ with BCI accuracy, 6) **mental effort ratings** taken at the end of each training session, had an average rating of 5.17 (*SD* = 1.85), ranging from 1 (very low) to 7 (fairly high), and a non-significant correlation ($r_s(10) = .414$, $p = .181$) with BCI accuracy, 7) **physical effort** ratings taken at the end of each training session, had an average rating of 2.25 (*SD* = .622), ranging from 1 (very low) to 3 (fairly low), and a non-significant correlation ($r_s(10) = .159$, $p = .621$) with BCI accuracy, 8**) overall 'hardness'** ratings taken at the end of each training session, had an average rating of 3.42 (*SD* = 1.31), ranging from 2 (very-fairly easy) to 6 (neutral-fairly hard), and a non-significant correlation ($r_s(10) = .102$, $p = .751$) with BCI accuracy.

For the neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C1 had an average value of 0.175 microvolts^2 (range: 0.04–1.36; *SD* = 0.373), and a non-significant correlation ($r_s(10) = .252$, $p = .430$) with BCI accuracy. C2 had an average value of 0.184 microvolts^2 (range: 0.04–1.29; *SD* = 0.380), and a non-significant correlation ($r_s(10) = .193$, $p = .549$) with BCI accuracy, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C1 had an average value of 0.068 microvolts^2

(range: 0–0.45; *SD* = 0.121), and a non-significant correlation ($r_s(10) = .301$, $p = .341$) with BCI accuracy. C2 had an average value of 0.086 microvolts² (range: 0.3–0.63; *SD* = 0.171), and a non-significant correlation ($r_s(10) = .324$, $p = .304$) with BCI accuracy, 3) **the ERS-ERD difference for C1 had an average value of -0.006 microvolts² (range: -0.13–0.21; *SD* = 0.078), and a significant positive correlation ($r_s(10) = .595$, $p < .05$) with BCI accuracy.** C2 had an average value of -0.003 microvolts² (range: -.11–0.04; *SD* = 0.037), and a non-significant correlation ($r_s(10) = 0$, $p = 1$) with BCI accuracy.

4.6.3 Participant A4: Recurring Measures in relation to session number

1) **Motivation** ratings, taken prior to the start of each training session demonstrated a non-significant correlation ($r_s(10) = .118$, $p = .714$) with session number, 2) **within-session fatigue (range: -1–2; *M* = 0.75 , *SD* = 1.22)** demonstrated a non-significant correlation ($r_s(10) =$.-.029, $p = .928$) with session number, 3) **frustration with device control** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = -.440$, $p = .152$) with session number, 4) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .323$, $p = .305$) with session number, 5) **physical effort** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .191$, p = .551) with session number, 6) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10) = .140$, $p =$ .642) with session number. For neurophysiological measures: 1) **peak amplitude of the sensorimotor rhythm at rest (ERS)** for C1, demonstrated a non-significant correlation ($r_s(10) =$ .182, $p = 572$) with session number. C2 demonstrated a non-significant correlation ($r_s(10) =$ .088, $p = .787$) with session number, 2) **amplitude of the sensorimotor rhythm minus the predicted noise level at rest (ERS)** for C1 demonstrated a non-significant correlation ($r_s(10) =$

.315, p = .318) with session number. C2 demonstrated a non-significant correlation ($r_s(10)$ = .141, p = .662) with session number, 3) the **ERS-ERD difference** for C1 demonstrated a non-significant correlation ($r_s(10)$ = .462, p = .130) with session number. C2 demonstrated a non-significant correlation ($r_s(10)$ = -.322, p = .308) with session number.

4.6.4 Participant A4: Recurring measures in relation to satisfaction ratings

1) **within-session fatigue** demonstrated a non-significant correlation ($r_s(10)$ = -.412, p = .184) with BCI satisfaction ratings, 2) **frustration with device control ratings taken at the end of each training session demonstrated a significant negative correlation ($r_s(10)$ = -.702, p <.05) with BCI satisfaction ratings**, 3) **metal effort ratings** taken at the end of each training session demonstrated a non-significant correlation ($r_s(10)$ = .284, p = .371) with BCI satisfaction ratings, 4) **physical effort ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10)$ = -.544, p = .068) with BCI satisfaction ratings**, 5) **Overall 'hardness'** ratings taken at the end of each training session demonstrated a non-significant correlation ($r_s(10)$ = -.272, p = .392) with BCI satisfaction ratings.

Chapter V: Discussion and Conclusion

The aim of this study was to assess the learning trajectories of individuals with ALS during (motor)-imagery-based BCI learning of a row-column AAC scanning paradigm, along with identifying how both initial and recurring person-centered factors relate to an individual's learning trajectory and overall satisfaction with BCI-AAC control. Due to the heterogenous nature of individuals with ALS, different profiles were identified that likely influenced how each individual progressed with BCI training. Along with establishing feasibility for BCI access to commercial row-column scanning AAC paradigms, this study identified multiple findings which

may inform the clinical implementation of BCI technology. Therefore, to support the clinical translation of BCI technology, study findings are interpreted in regard the feasibility of BCI access to commercial row-column AAC displays, along with how results may inform BCI trials, and other feature matching considerations for BCI assessment and intervention.

5.1 Feasibility for BCI access to commercial row-column scanning paradigms

Overall findings from this project support that (motor) imagery-based BCI switch access to a commercial AAC row-column scanning paradigm is feasible for individuals with ALS. This finding builds upon the work of Brumberg et al., (2016), Scherer et al., (2015), and Friedrich et al., (2009), expanding online BCI access to larger matrices commonly utilized for AAC access. In further detail, BCI learning trajectories for this BCI device were variable both between and within participants for those with ALS. However, only A2 was unable to demonstrate *either* a BCI performance in the range of neurotypical peers, or an improving BCI learning trajectory. In contrast, for more than one session A1 and A4 were able to establish levels of BCI control within the range of neurotypical controls (range: .3825–.7339) after the initial session for T3 was removed as an outlier due to initial BCI learning. Specifically, A1 achieved accuracies of .445, .423, .522 and .544 and .425 for sessions 2, 3, 6, 7 and 12 respectively, and A4 achieved accuracies of .407 and .468 for sessions 10 and 11 respectively. Furthermore, A3 and A4 were able to demonstrate an improving BCI learning trajectory, and while the average BCI performance was low for A3 across sessions (M= -.01, SD = .096), these findings highlight that an individual with severe physical impairments may demonstrate BCI learning, though extensive training may be needed for proficiency. It is important to note however, that while BCI performance for A3 may be sub-threshold for functional BCI use (i.e., they could not spell a 4 to 5 letter word without multiple spelling errors which rendered the word largely unreadable),

individualized adaptions to the BCI system were not performed during BCI training to allow for comparison across participants. For instance, due to disease severity, A3 had multiple muscle spasms throughout BCI calibration and training, which likely decreased BCI performance accuracy. Therefore, adaptions to improve signal processing such as online removal of muscle artifacts, combining other signals such as the contingent negative variation in BCI decoding (Brumberg et al., 2016), may increase overall BCI performance values to a more functional level. Therefore, further research regarding signal processing for this BCI system is warranted. Nevertheless, interpreting these findings in a feature matching framework, an attention modulated BCI system such as the visual P300-speller may provide A3 with a more familiar AAC interface, and lessen the burden associated with BCI learning, as she already uses an eye-gaze AAC system to support communication, environmental control, and internet browsing. While in comparison to eye gaze, P300 grid systems require less precise eye movements, grid based P300-based BCIs parallel eye-gaze access as P300 BCI performance is improved by use of an overt attention strategy, where the individual focuses their eyes, and attention on the item they wish to select in comparison to a covert strategy, which utilizes a peripheral focus (e.g., Brunner et al., 2010).

5.2 Implications of findings for BCI assessment

In the following section a brief review of clinical takeaways is provided, with further explanation supporting these conclusions provided in section 5.2.2.

5.2.1 Participant Profiles and Clinical takeaways for BCI feature matching

This investigation assessed a range of factors related to an individual's unique profile including cognitive, and motor skills, along with neurophysiological measures of BCI related

EEG activity. While the generalization of findings is restricted due to the limited sample size, successful BCI access through motor execution was positively supported by an individual's physical motor abilities, as both participants A1 and A2 achieved the highest levels of BCI success. That physical motor abilities may support BCI success, even for those with cognitive impairment, supports the notion that similar to existing AAC methods, timely assessment and intervention may help support BCI success, Specifically, improved BCI success may be supported by beginning training before functional motor abilities are severely impaired, by possibly lowering cognitive burdens associated with motor imagery performance and learning of a new communication method and allowing BCI devices to adapt to the individuals changing needs and abilities across the life span. Therefore, while motor imagery control tasks are the main focus of sensorimotor BCI research and development, further research is warranted into BCI control via motor execution to support BCI success and ability-based BCI and AAC designs that utilize an individual's current motor skills.

Regarding BCI assessment measures, while results from the BCI screener remain unclear, promising findings from motor sections of the BCI screener along with cognitive score differences separating those demonstrating a positive BCI learning trajectory from those who did not, support the need for continued investigation of BCI specific screening tools to help standardize BCI assessment procedures for identifying person centered factors related to BCI control. In addition, further investigation on the effects of medications and food intake on BCI performance may help elucidate the why participant A2 was unable to establish stable BCI performance, or a positive learning trajectory. Finally, due to correlations between neurophysiological measures of event related synchronization (ERS), and the difference between event related synchronization and desynchronization (ERS-ERD) with BCI performance, this

dissertation study continues to support the use of neurophysiological measures in BCI assessment. However, as neurophysiological measures may change across sessions, more than a single time point may be needed to fully characterize an individual's profile and account for performance variability (e.g., Thompson, 2018).

5.2.2 Assessment findings

Previously, functional motor abilities were not shown to be related to the ability of individuals with ALS to perform imagined movements utilized for BCI control (Geronimo et al., 2016; Kasahara et al., 2012). However, as our BCI was controlled by motor execution, the highest levels of BCI performance were achieved by participants A1 and A4 who both demonstrated the least level of motor impairment in the limb utilized for BCI control (i.e., A1 upper limb, and A4 lower limb). Relevant differences in motor ability between participants are especially apparent in the qualitative descriptions obtained by the BCI screener indicating no impairment of the upper limb for A1, and A4 reporting his legs were 'still strong', being ambulatory without assistance. In comparison to the BCI screener, other measures utilized for assessment of motor function were limited in elucidating differences in motor function between participants that were relevant to BCI control. Specifically, while the MACS, and BFMF were able to quantify differences in upper limb ability, they do not assess function of the lower limb, which may be utilized for BCI control. Furthermore, the ALS-FRS assesses a range of functional motor abilities, including those related to upper, lower and bulbar function. Therefore, while total ALS-FRS score highlights that A3 had the highest level of limb motor impairments, specific differences in motor abilities between participants is less clear (e.g., A1 had difficulties with bulbar motor functions, and A2 limb motor functions, though they achieved similar scores of 33 and 34 respectively). In addition, it is possible that self-ratings of motor function may be

affected by environmental support. For instance, while descriptively A4 had decreased levels of motor impairment in comparison to A2, he rated increased motor impairments on the ALS-FRS, based on the support provided by his wife (e.g., she would cut up his food). In contrast, A2 still lived independently, and therefore, rated his impairments as less severe as he was still managing to independently complete functional tasks, even if with large amounts of difficulty. Taken together these findings highlight the importance of individualized assessment of motor function as guided by the tools such as the BCI screener.

As the cognitive section of the BCI screener is not designed to assess an individual's level of impairment, scores for the cognitive section of the BCI screener were high (range: 22–24), indicating the participants possessed BCI related skills. However, it is interesting to note that both A1 and A2 did not demonstrate a consistent learning trajectory and each missed two points on the BCI screener, losing one point in the area of attention and working memory, and one point in the area of cognitive motor learning and abstract problem solving. Therefore, while the relationship between BCI screener scores and BCI performance remains unclear, taken together with the findings for the motor portion of the BCI screener, further research into the development of BCI specific assessment tools is warranted. In addition, ALS-CBS scores reveal that both A1 and A4 presented with a suspicion for cognitive impairment, as characterized by ALS-CBS scores below 17 (Wooley, 2014). However, participants A1 and A4 achieved the highest levels of BCI performance. The finding of greater BCI performance for participants with ALS who have suspicion for cognitive deficits is in contrast to previous findings for BCI devices controlled by imagined movements, which found diminished BCI performance for those with lower ALS-CBS scores (Geronimo et al., 2016). However, participants with suspected cognitive impairment in our study also presented with the least physical impairment in the limb used for

BCI control. It is plausible providing an individual with a motor (imagery)-based BCI device before loss of physical movement may lower the cognitive demands associated with the abstract nature of imagery performance. Therefore, starting BCI intervention early, before loss of motor function, may allow time for an individual to begin establishing BCI mastery in the hope that learned skills support BCI control through imagery strategies later in the disease course. However, while for the present BCI system, physical motor movements supported BCI success, even in the presence of cognitive impairment, further research is needed to assess the effects of timely intervention and motor abilities in a larger population of individuals who may use BCI, along with the associated impacts on BCI performance and quality of life across the life span.

Neurophysiological measures including peak ERS, peak ERS minus the predicted noise level, and ERS-ERD difference were variable both within and between participants. Prior to BCI use, A1 demonstrated the highest amplitudes for each measure and achieved, on average, the highest level of BCI accuracy, in contrast to A3, who presented with the lowest amplitudes for peak ERS and ERS-ERD difference and demonstrated the lowest average BCI performance. However, the lowest amplitude for the ERS-noise measure was noted for A4 who achieved the second highest level of BCI performance. Therefore, these findings generally fit the expected pattern, and continue to support the role of the ERS and ERS-ERD measures in predicting BCI performance. When looking across sessions, a significant correlation between left hand peak ERS and BCI performance was identified for A2. Surprisingly however, across sessions, A3 presented with the highest average amplitudes for both ERS measures. Exactly why these amplitude changes occurred between initial assessment and BCI training are currently unclear but may be due to factors such as increased artifact in the signal due to spasms, or variations in neurological activity associated with disease progression. However, this variability in

performance supports recent discussion that multiple data points may be needed to fully characterize an individual's EEG profile due to day-to-day fluctuations (Thompson et al., 2018). Finally, for the ERS-ERD measure, A1 demonstrated the largest difference across sessions. In addition, ERD-ERS values were significantly correlated to BCI performance for A4 at location C1. Therefore, though there appear to be individual differences in neurophysiological measures, findings support the use of both ERS measures at rest and ERS-ERD difference measures for BCI assessment of individuals with ALS.

A3 demonstrated an improving learning trajectory that may be increased in magnitude by BCI adaptions such as online filtering of muscle artifacts related to spasms. However, based upon overall assessment findings, it is unclear why A2 was unable to demonstrate a BCI learning trajectory or achieve consistent performance similar to that of neurotypical peers. Of clinical consideration, during BCI training A2 was also participating in a Radicava ® drug trial requiring cycles where he received daily infusions for a two-week period following by two weeks of rest. Currently, there is limited research on the effects of medications on BCI performance (e.g., Pitt & Brumberg, 2018a), and the influence of Radicava ® on BCI related signals is unknown. Furthermore, A2 did not eat for an average of 9.72 hours prior to BCI training sessions, possibly decreasing his energy levels and mental focus (Geisler, 1990). Low energy levels may have been further compounded by efforts taken to receive Radicava ® infusions. Taken together, these medication and cognitive factors may impair abilities to gain BCI control, and future research should seek to identify the effects of ALS medications such as Radicava ®, along with energy levels associated with decreased intake and dysphagia on BCI performance.

5.2.3 Length of BCI trials

Each participant with ALS demonstrated their own unique BCI performance trajectory across the twelve training sessions. However, while more than one session is needed to make an informed clinical decision regarding suitability for a BCI device controlled by motor execution, the BCI performance needed to demonstrate whether growth is expected for each participant can be approximated in around 5, 20-minute sessions each including approximately 300 trials. Along with consideration of the individuals own unique preference, requiring approximetly 5 sessions to make informed clinical decision about (motor)-imagery-based BCI suitability helps bring the duration of BCI trials to a feasible range for clinical decision making and implementation. Regarding approximation of an individual's learning trajectory, satisfactory/encouraging BCI performances were associated with the following characteristics within the first 5 BCI training sessions:

1) stable BCI performance, similar to that of neurotypical peers, for at least 2 consecutive sessions (as with A1).
2) beginning and maintaining an improving BCI performance trajectory within the first 5 sessions (as with A3 and A4). However, extended trials may be necessary for individuals showing variable/low BCI performance (such as A3), allowing time for further individualization of BCI parameters to improve BCI performance stability and overall performance magnitude. Random BCI performance during sessions 1-5 without a positive learning trajectory, or only one or two non-consecutive sessions of BCI performance comparative to neurotypical peers was not indicative of success (as with A2).

While this study provides preliminary guidelines regarding trials length for event-related desynchronization-based BCIs controlled by motor execution, motor imagery-based BCI access may require extended training times possibly increasing frustrations associated with motor learning (e.g., Nijboer et al., 2010). Further work is needed to create training protocols that minimize frustration, along with establishing these findings and investigating assessment guidelines for BCIs controlled through motor imagery, or attention modulation (e.g., P300 or SSVEP). Extending the methods and findings of this dissertation to include clinical guidelines governing the full range of BCI modalities is necessary to support feature matching-based BCI assessment and BCI access for individuals who are unable to begin BCI trials before the absence of physical motor movement.

5.3 Implications of findings for BCI intervention

In the following section a brief review of clinical takeaways is provided, with further explanation supporting these conclusions provided in section 5.3.2.

5.3.1 Clinical takeaways for BCI intervention

Traditionally BCI intervention studies focus on copy spelling tasks and accuracy-based performance outcomes (Pitt et al., in press). While these BCI paradigms have created a foundation for the transition of BCI into clinical practice, these dissertation findings support the use of tasks such as free spelling in BCI trials, along with incorporating a range of person-centered factors in understanding performance outcomes, and user satisfaction, such as multiple measures of fatigue (e.g., general level of fatigue, and mental and physical effort), and levels of frustration. Finally, associations between decreased mental effort and improving levels of BCI

performance possibly support the use of utilizing natural/relaxed levels effort when mastering (motor)-imagery-based BCI control (Witte et al., 2013).

5.3.2 Intervention findings

On average, ratings of motivation were high for all participants with ALS. Participants reported a range of factors influencing their high levels of motivation including, the hope of using BCI as a communication method, interest in BCI technology, and a desire to 'help science'. However, motivation ratings significantly decreased across sessions for A2 and A3, possibly due to a lack of stable BCI control of functional levels. While pre session ratings of motivation were not correlated to BCI performance in this study, possibly due to participants high levels of baseline motivation, previous findings have identified motivation as an important aspect in achieving BCI control (e.g., Kleih & Kubler, 2015). Therefore, consideration of how to increase motivation during the early stages of motor learning may be important for helping support BCI success (e.g., error free learning). While traditionally BCI studies have focused on copy spelling tasks, A4 reported his high levels of motivation were generally driven by his desire to attempt free spelling tasks and move to the next level of functional independence in BCI control. Free spelling tasks were planned for completion during this investigation once a stable level of substantial BCI accuracy was achieved through copy spelling training. However, no participants with ALS achieved stable BCI performance of this level. Therefore, the incorporation of functional communication tasks beyond copy spelling may support sustained levels of BCI motivation helping improve outcomes for multi-session BCI trials (e.g., Pitt, et al., in press).

The focus on copy spellings in BCI paradigms is traditionally accompanied by outcome measures focused on BCI accuracy and performance (e.g., Pitt, et al., in press). This research

focus, while narrow, has provided a foundation for the clinical translation of BCI research, with studies beginning to expand to evaluate a range of person-centered factors associated with BCI performance (e.g., Peters et al., 2016). Building upon this foundation, study findings support that factors influencing satisfaction may differ between participants, with satisfaction ratings positively correlated to performance for A1 and A3, but primarily driven by levels of frustration for participants A2 and A4, though for A4 lower levels of physical effort also approached significance (p=.068).Therefore, future BCI research and intervention paradigms may seek to include outcome measures, such as frustration and physical effort ratings, to help elucidate primary factors influencing an individual's satisfaction with BCI technology to optimize training strategies and inform future research directions in BCI development. Of further consideration, this study revealed that the incorporation of fatigue ratings for BCI intervention paradigms require further consideration. Due to previous reports that BCI control requires high levels of effort (e.g., Chavarriaga et al., 2017), it was expected that within session fatigue ratings would also be increased. However, surprisingly, while average ratings of mental effort ratings across participants ranged from neutral (5) to fairly high (7), average with-in session fatigue ratings were very low, ranging from -1 to 1. Negative within session fatigue ratings, along with participant report from A3, also indicate some participants felt less fatigued following BCI use, possibly due to participation in an engaging activity. Furthermore, differences between mental effort and within session fatigue may be due to differences in participants definition of the term fatigue, with one participant (A3) indicating it was generally synonymous with mental effort, and three participants indicating the term fatigue better reflects physical effort which was generally low for this BCI system. Therefore, along with ratings of frustration, future BCI trials should provide different options of fatigue and effort (e.g., mental effort, physical effort; e.g., Peters et

al., 2016) to allow for individualized and precise ratings of person-centered factors associated with BCI use. In addition, future research may seek to explore what underlying factors are captured by ratings of fatigue for various BCI systems, to help ensure individuals are matched to devices which minimize workload burdens upon the individual. Finally, mental effort ratings significantly decreased across sessions for A3 along with improved BCI performance and showed a moderate (r_s =-.478 to -.479) negative trend with BCI performance for A1, and A2. In addition, participants A1, and A2 indicated improved BCI success when 'effortless' or more natural effort levels were used versus extreme effort levels. Therefore, while further research is needed, helping participants not to overthink BCI motor learning may help decrease overall levels of fatigue, effort, and frustration, improving BCI acceptance.

5.4 Limitations

Though the findings of this study outlined multiple factors for consideration in BCI assessment and intervention, along with demonstrating the feasibility of BCI access to commercial AAC paradigms, the limited sample size of this study means further work is needed to confirm these findings, develop clinical guidelines for BCI devices based on motor execution and imagery, and expand results to inform BCI assessment of other BCI devices. While this limited sample size of individuals with ALS was sufficient to lay the clinical groundwork, further work is needed to generalize findings to other populations of individuals who may use BCI as an access method (e.g., brain stem stroke, upper spinal cord injury, locked in syndrome, cerebral palsy). Finally, it is important to note that to facilitate comparison across participants, apart from allowing A4 to use his lower limb for BCI control due to increased strength, the BCI system was not individualized or adapted to meet individual needs across the study. Therefore, future research evaluating signal processing techniques, feedback methods, and training

paradigms (e.g., feedback, intensity) may help support overall increase in BCI performance, and ratings of person-centered factor associated with BCI performance and satisfaction.

References

Abdulkader, S. N., Atia, A., & Mostafa, M.-S. M. (2015). Brain computer interfacing: Applications and challenges. *Egyptian Informatics Journal, 16*(2), 213-230.

Ahn, M., Ahn, S., Hong, J. H., Cho, H., Kim, K., Kim, B. S., . . . Jun, S. C. (2013). Gamma band activity associated with BCI performance: simultaneous MEG/EEG study. *Frontiers in Human Neuroscience, 7*, 848.

Ahn, M., Cho, H., Ahn, S., & Jun, S. C. (2013). High theta and low alpha powers may be indicative of BCI-illiteracy in motor imagery. *PLoS One, 8*(11), e80886.

Ahn, M., Cho, H., Ahn, S., & Jun, S. C. (2018). User's Self-Prediction of Performance in Motor Imagery Brain-Computer Interface. *Frontiers in Human Neuroscience, 12*, 59.

Ahn, M., & Jun, S. C. (2015). Performance variation in motor imagery brain-computer interface: a brief review. *Journal of Neuroscience Methods, 243*, 103-110.

Akcakaya, M., Peters, B., Moghadamfalahi, M., Mooney, A. R., Orhan, U., Oken, B., . . . Fried-Oken, M. (2014). Noninvasive brain-computer interfaces for augmentative and alternative communication. *IEEE Reviews in Biomedical Engineering, 7*, 31-49.

Allison, B., McFarland, D., Schalk, G., Zheng, S., Jackson, M., & Wolpaw, J. (2008). Towards an independent brain-computer interface using steady state visual evoked potentials. *Clinical Neurophysiology, 119*(2), 399-408.

Arico, P., Aloise, F., Schettini, F., Salinari, S., Mattia, D., & Cincotti, F. (2014). Influence of P300 latency jitter on event related potential-based brain-computer interface performance. *Journal of Neural Engineering, 11*(3), 035008.

Bamdadian, A., Guan, C., Ang, K. K., & Xu, J. (2014). The predictive role of pre-cue EEG rhythms on MI-based BCI classification performance. *Journal of Neuroscience Methods,*

235, 138-144.

Baykara, E., Ruf, C. A., Fioravanti, C., Kathner, I., Simon, N., Kleih, S. C., . . . Halder, S. (2016). Effects of training and motivation on auditory P300 brain-computer interface performance. *Clinical Neurophysiology, 127*(1), 379-387.

Beckung, E., & Hagberg, G. (2002). Neuroimpairments, activity limitations, and participation restrictions in children with cerebral palsy. *Developmental Medicine & Child Neurology*, *44*(5), 309-316.

Beeldman, E., Raaphorst, J., Klein Twennaar, M., de Visser, M., Schmand, B. A., & de Haan, R. J. (2016). The cognitive profile of ALS: a systematic review and meta-analysis update. *Journal of Neurology, Neurosurgery, and Psychiatry, 87*(6), 611-619.

Beukelman, D., & Ansel, B. (1995). Research priorities in augmentative and alternative communication. *Augmentative and Alternative Communication, 11*(2), 131-134.

Beukelman, D. R., Fager, S., Ball, L., & Dietz, A. (2007). AAC for adults with acquired neurological conditions: a review. *Augmentative and Alternative Communication, 23*(3), 230-242.

Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., ... & Flor, H. (1999). A spelling device for the paralysed. *Nature*, *398*(6725), 297-298.

Blain-Moraes, S., Schaff, R., Gruis, K. L., Huggins, J. E., & Wren, P. A. (2012). Barriers to and mediators of brain-computer interface user acceptance: focus group findings. *Ergonomics, 55*(5), 516-525.

Blankertz, B., Dornhege, G., Krauledat, M., Muller, K. R., Kunzmann, V., Losch, F., & Curio, G. (2006). The Berlin brain–computer interface: EEG-based communication without subject training. *IEEE Transactions on neural systems and rehabilitation engineering,*

14(2), 147–152.

Blankertz, B., Sannelli, C., Halder, S., Hammer, E., Kübler, A., Müller, K., . . . Dickhaus, T. (2010). Neurophysiological predictor of SMR-based BCI performance. *Neuroimage, 51*(4), 1303-1309.

Bobrova, E. V., A. A. Frolov, and V. V. Reshetnikova. (2018). Methods and approaches to optimizing control using a brain–computer interface system by healthy subjects and patients with motor disorders. *Neuroscience and Behavioral Physiology*, *48*(9), 1041-1052.

Bobrova, E. V., Reshetnikova, V. V., Volkova, K. V., & Frolov, A. A. . (2018). Effects of emotional stability on success in learning to control a brain–computer interface. *Neuroscience and Behavioral Physiology, 48*(9), 1114-1119.

Brandl, S., Höhne, J., Müller, K. R., & Samek, W. (2015, April). Bringing BCI into everyday life: Motor imagery in a pseudo realistic environment. In *2015 7th International IEEE/EMBS Conference on Neural Engineering,* 224-227.

Brumberg, J. S., Burnison, J. D., & Pitt, K. M. (2016). Using motor imagery to control brain–computer interfaces for communication. In D. D. Schmorrow & C. M. Fidopiastis (Eds.), Foundations of augmented cognition: Neuroergonomics and operational neuroscience (pp. 14–25). Cham, Switzerland: Springer.

Brumberg, J. S., Nguyen, A., Pitt, K. M., & Lorenz, S. D. . (2018). Examining sensory ability, feature matching and assessment-based adaptation for a brain–computer interface using the steady-state visually evoked potential. *Disability and Rehabilitation: Assistive Technology*, 1-9.

Brumberg, J. S., Pitt, K. M., & Burnison, J. D. (2018). A Noninvasive Brain-Computer Interface

for Real-Time Speech Synthesis: The Importance of Multimodal Feedback. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26*(4), 874-881.

Brumberg, J. S., Pitt, K. M., Mantie-Kozlowski, A., & Burnison, J. D. (2018). Brain-Computer Interfaces for Augmentative and Alternative Communication: A Tutorial. *American Journal of Speech-Language Pathology, 27*(1), 1-12.

Brunner, P., Joshi, S., Briskin, S., Wolpaw, J. R., Bischof, H., & Schalk, G. (2010). Does the 'P300' speller depend on eye gaze? *Journal of Neural Engineering, 7*(5), 056013.

Burde, & Blankertz, B. (2006). Is the locus of control of reinforcement a predictor of brain-computer interface performance? In: Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course 2006. Verlag der Technischen Universit¨at Graz, 76–77.

Campbell, P., Milbourne, S., Dugan, L., & Wilcox, M. (2006). A review of evidence on practices for teaching young children to use assistive technology devices. *Topics in Early Childhood Special Educatio*n, *26*(1), 3-13.

Cedarbaum, J. M., & Stambler, N. (1997). Performance of the amyotrophic lateral sclerosis functional rating scale (ALSFRS) in multicenter clinical trials. *Journal of the Neurological Sciences*, 152, s1–s9.

Chavarriaga, R., Fried-Oken, M., Kleih, S., Lotte, F., & Scherer, R. (2017). Heading for new shores! Overcoming pitfalls in BCI design. *Brain-Computer Interfaces*, *4*, 60-73.

Chiò, A., Pagani, M., Agosta, F., Calvo, A., Cistaro, A., & Filippi, M (2014). Neuroimaging in amyotrophic lateral sclerosis: insights into structural and functional changes. *The Lancet Neurology, 13*(12), 1228-1240.

Combaz, A., Chatelle, C., Robben, A., Vanhoof, G., Goeleven, A., Thijs, V., . . . Laureys, S.

(2013). A comparison of two spelling brain-computer interfaces based on visual P3 and SSVEP in locked-in syndrome. *PLoS One, 8*(9), e73691.

Craje, C., van Elk, M., Beeren, M., van Schie, H. T., Bekkering, H., & Steenbergen, B. (2010). Compromised motor planning and motor I=imagery in right H=hemiparetic cerebral palsy. *Research in Developmental Disabilities, 31*(6), 1313-1322.

Crockford, C., Newton, J., Lonergan, K., Chiwera, T., Booth, T., Chandran, S., . . . Abrahams, S. (2018). ALS-specific cognitive and behavior changes associated with advancing disease stage in ALS. *Neurology*, *91*(15), e1370-e1380.

da Silva-Sauer, L., Valero-Aguayo, L., de la Torre-Luque, A., Ron-Angevin, R., & Varona-Moya, S. (2016). Concentration on performance with P300-based BCI systems: A matter of interface features. *Applied ergonomics, 52*, 325-332.

Daly, I., Billinger, M., Laparra-Hernandez, J., Aloise, F., Garcia, M. L., Faller, J., . . . Muller-Putz, G. (2013). On the control of brain-computer interfaces by users with cerebral palsy. *Clinical Neurophysiology, 124*(9), 1787-1797.

Daly, J., Armstrong, E., Thomson, E., Andreas, P., & Martin, S. (2015). P300 brain computer interface control after an acquired brain injury. *International Journal on recent and innovation trends in computing and communication*, *3*(1), 318-325.

Darvishi, S., Abbott, D., & Baumert, M. (2015). Prediction of motor imagery based brain computer interface performance using a reaction time test. *In Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, 2880-2883.

Donchin, E., Spencer, K. M., & Wijesinghe, R. (2000). The mental prosthesis: assessing the of a P300-based brain-computer interface. *IEEE Transactions on Rehabilitation*

Engineering, 8(2), 174-179.

Doyle, M., & Phillips, B. (2009). Trends in augmentative and alternative communication use by individuals with amyotrophic lateral sclerosis. *Augmentative and Alternative Communication, 17*(3), 167-178.

Eliasson, A. C., Krumlinde-Sundholm, L., Rösblad, B., Beckung, E., Arner, M., Öhrvall, A. M., & Rosenbaum, P. (2006). The Manual Ability Classification System (MACS) for children with cerebral palsy: scale development and evidence of validity and reliability. *Developmental medicine and child neurology*, *48*(7), 549-554.

Elvrum, A. K. G., Andersen, G. L., Himmelmann, K., Beckung, E., Öhrvall, A. M., Lydersen, S., & Vik, T. (2016). Bimanual fine motor function (BFMF) classification in children with cerebral palsy: aspects of construct and content validity. *Physical & occupational therapy in pediatrics*, *36*(1), 1-16

Fager, S., Bardach, L., Russell, S., & Higginbotham, J. (2012). Access to augmentative and alternative communication: new technologies and clinical decision-making. *Journal of pediatric rehabilabilitation and medicine, 5*(1), 53-61.

Fager, S. K. (2018). Alternative access for adults who rely on augmentative and alternative communication. *ASHA Perspectives*, *3*(12), 6-12.

Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and clinical neurophysiology, 70*(6), 510-523.

Fiori, F., Sedda, A., Ferre, E. R., Toraldo, A., Querzola, M., Pasotti, F., . . . Bottini, G. (2013). Exploring motor and visual imagery in Amyotrophic Lateral Sclerosis. *Experimental brain research, 226*(4), 537-547.

Fried-Oken, M., Mooney, A., Peters, B., & Oken, B. (2013). A clinical screening protocol for the RSVP Keyboard brain-computer interface. *Disability and Rehabilitation: Assistive Technology, 10*(1), 11-18.

Fried-Oken, M., Mooney, A., & Peters, B. (2015). Supporting communication for patients with neurodegenerative disease. *NeuroRehabilitation, 37*(1), 69-87.

Friedrich, E. V., McFarland, D. J., Neuper, C., Vaughan, T. M., Brunner, P., & Wolpaw, J. R. (2009). A scanning protocol for a sensorimotor rhythm-based brain-computer interface. *Biological Psychology, 80*(2), 169-175.

Friedrich, E. V., Scherer, R., & Neuper, C. (2013). Long-term evaluation of a 4-class imagery-based brain-computer interface. *Clinical Neurophysiology, 124*(5), 916-927.

García, L., Ron-Angevin, R., Loubière, B., Renault, L., Le Masson, G., Lespinet-Najib, V., & André, J. M. (2017). A comparison of a brain-computer interface and an eye tracker: is there a more appropriate technology for controlling a virtual keyboard in an ALS patient? In *International Work-Conference on Artificial Neural Networks*, 464-473.

Geisler, M. W., & Polich, J. . (1990). P300 and time of day: circadian rhythms, food intake, and body temperature. *Biological Psychology, 31*(2), 117-136.

Geronimo, A., Sheldon, K. E., Broach, J. R., Simmons, Z., & Schiff, S. J. (2017). Expansion of C9ORF72 in amyotrophic lateral sclerosis correlates with brain-computer interface performance. *Scientific Reports, 7*(1), 8875.

Geronimo, A., Simmons, Z., & Schiff, S. J. (2016). Performance predictors of brain-computer interfaces in patients with amyotrophic lateral sclerosis. *Journal of Neural Engineering, 13*(2), 026002.

Geronimo, A., Stephens, H. E., Schiff, S. J., & Simmons, Z. (2015). Acceptance of brain-

computer interfaces in amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 16*(3-4), 258-264.

Goldstein, L. H., & Abrahams, S. (2013). Changes in cognition and behaviour in amyotrophic lateral sclerosis: nature of impairment and implications for assessment. *The Lancet Neurology, 12*(4), 368-380.

Gosnell, J., Costello, J., & Shane, H. (2011). Using a clinical approach to answer "what communication apps should we use?". *SIG 12 Perspectives on Augmentative and Alternative Communication, 20*(3), 87-96.

Gregg, M., Hall, C., & Butler, A. (2010). The MIQ-RS: a suitable option for examining movement imagery ability. *Evidence-Based Complementary and Alternative Medicine*, *7*(2), 249-257.

Green, J. R., Yunusova, Y., Kuruvilla, M. S., Wang, J., Pattee, G. L., Synhorst, L., ... & Berry, J. D. . (2013). Bulbar and speech motor assessment in ALS: Challenges and future directions. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 14*(7-8), 494-500.

Grosse-Wentrup, M., & Schölkopf, B. (2012). High gamma power predicts performance in sensorimotor-rhythm brain computer interfaces. *Journal of neural engineering, 9*(4), 046001.

Grosse-Wentrup, M., Schölkopf, B., (2013). A review of performance variations in SMR based brain–computer interfaces (BCIs). In: Guger, C., Allison, B., Edlinger, G. (Eds.), Brain–Computer Interface Research. Springer, pp. 39–51.

Halder, S., Agorastos, D., Veit, R., Hammer, E. M., Lee, S., Varkuti, B., . . . Kubler, A. (2011). Neural mechanisms of brain-computer interface control. *Neuroimage, 55*(4), 1779-1790.

Halder, S., Ruf, C. A., Furdea, A., Pasqualotto, E., De Massari, D., van der Heiden, L., . . . Matuz, T. (2013). Prediction of P300 BCI aptitude in severe motor impairment. *PLoS One, 8*(10), e76148.

Halder, S., Takano, K., & Kansaku, K. (2018). Comparison of four control methods for a five-choice assistive technology. *Frontiers in Human Neuroscience, 12*, 228.

Halder, S., Varkuti, B., Bogdan, M., Kübler, A., Rosenstiel, W., Sitaram, R., & Birbaumer, N. (2013). Prediction of brain-computer interface aptitude from individual brain structure. *Frontiers in Human Neuroscience, 7*, 105.

Hammer, E. M., Halder, S., Blankertz, B., Sannelli, C., Dickhaus, T., Kleih, S., . . . Kubler, A. (2012). Psychological predictors of SMR-BCI performance. *Biological Psycholgy, 89*(1), 80-86.

Hammer, E. M., Halder, S., Kleih, S. C., & Kübler, A. (2018). Psychological predictors of visual and auditory P300 brain-computer interface performance. *Frontiers in Neuroscience, 12*, 307.

Hammer, E. M., Kaufmann, T., Kleih, S. C., Blankertz, B., & Kubler, A. (2014). Visuo-motor coordination ability predicts performance with brain-computer interfaces controlled by modulation of sensorimotor rhythms (SMR). *Frontiers in human Neuroscience, 8*, 574.

He, S., Huang, Q., & Li, Y. . (2016, June). Toward improved P300 speller performance in outdoor environment using polarizer. *In Intelligent Control and Automation, 2016 12th World Congress on,* 3172-3175.

Hétu, S., Grégoire, M., Saimpont, A., Coll, M. P., Eugène, F., Michon, P. E., & Jackson, P. L. (2013). The neural network of motor imagery: an ALE meta-analysis. *Neuroscience & Biobehavioral Reviews, 37*(5), 930-949.

Higashi, H., Rutkowski, T. M., Washizawa, Y., Cichocki, A., & Tanaka, T. (2011). EEG auditory steady state responses classification for the novel BCI. In proceedings of the *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 4576-4579.

Higger, M., Quivira, F., Akcakaya, M., Moghdamfalahi, M., Nezamfar, H., Cetin, M., & Erdogmus, M. (2017). Recursive Bayesian Coding for BCIs. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(6), 704-714.

Hill, K., Kovacs, T., & Shin, S. (2015). Critical issues using brain-computer interfaces for augmentative and alternative communication. *Archives of Physical Medicine and Rehabilitation, 96*(3), S8-15.

Hill, N. J., Ricci, E., Haider, S., McCane, L. M., Heckman, S., Wolpaw, J. R., & Vaughan, T. M. (2014). A practical, intuitive brain-computer interface for communicating 'yes' or 'no' by listening. *Journal of Neural Engineering, 11*(3), 035003.

Holz, E. M., Botrel, L., Kaufmann, T., & Kubler, A. (2015). Long-term independent brain-computer interface home use improves quality of life of a patient in the locked-in state: a case study. *Archives of Physical Medicine and Rehabilitation, 96*(3), S16-26.

Huggins, J. E., Wren, P. A., & Gruis, K. L. (2011). What would brain-computer interface users want? Opinions and priorities of potential users with amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis, 12*(5), 318-324.

Ikegami, S., Takano, K., Wada, M., Saeki, N., & Kansaku, K. (2012). Effect of the Green/Blue Flicker Matrix for P300-Based Brain-Computer Interface: An EEG-fMRI Study. *Frontiers in Neurology, 3*, 113.

Jagaroo, V., & Wilkinson, K. (2009). Further Considerations of visual cognitive neuroscience in

aided AAC: The potential role of motion perception systems in maximizing design display. *Augmentative and Alternative Communication, 24*(1), 29-42.

Jeunet, C., Jahanpour, E., & Lotte, F. (2016). Why Standard Brain-Computer Interface (BCI) Training Protocols Should be Changed: An Experimental Study. *Journal of Neural Engineering, 13*(3), 036024.

Jeunet, C., N'Kaoua, B., Subramanian, S., Hachet, M., & Lotte, F. (2015). Predicting Mental Imagery-Based BCI Performance from Personality, Cognitive Profile and Neurophysiological Patterns. *PLoS One, 10*(12), e0143962.

Jeunet, C., N'Kaoua, B., & Lotte, F. . (2016). Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates. *In Progress in Brain Research*, *228*, 3-35.

Kageyama, Y., Hirata, M., Yanagisawa, T., Shimokawa, T., Sawada, J., Morris, S., . . . Yoshimine, T. (2014). Severely affected ALS patients have broad and high expectations for brain-machine interfaces. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 15*(7-8), 513-519.

Kasahara, K., DaSalla, C. S., Honda, M., & Hanakawa, T. (2015). Neuroanatomical correlates of brain-computer interface performance. *Neuroimage, 110*, 95-100.

Kasahara, K., Hoshino, H., Furusawa, Y., Sayo DaSalla, C., Honda, M., Murata, M., & Hanakawa, T. (2018). Initial experience with a sensorimotor rhythm-based brain-computer interface in a Parkinson's disease patient. *Brain-Computer Interfaces*, 1-9.

Kasahara, T., Terasaki, K., Ogawa, Y., Ushiba, J., Aramaki, H., & Masakado, Y. (2012). The correlation between motor impairments and event-related desynchronization during motor imagery in ALS patients. *BMC neuroscience, 13*(1), 66.

Kathner, I., Kubler, A., & Halder, S. (2015). Comparison of eye tracking, electrooculography and an auditory brain-computer interface for binary communication: A case study with a participant in the locked-in state. *Journal of NeuroEngineering and Rehabilitation*, 12(1), 76.

Kathner, I., Ruf, C. A., Pasqualotto, E., Braun, C., Birbaumer, N., & Halder, S. (2013). A portable auditory P300 brain-computer interface with directional cues. *Clinical Neurophysiology, 124*(2), 327-338.

Kathner, I., Wriessnegger, S. C., Muller-Putz, G. R., Kubler, A., & Halder, S. (2014). Effects of mental workload and fatigue on the P300, alpha and theta band power during operation of an ERP (P300) brain-computer interface. *Biological Psychology, 102*(1), 118-129.

Kaufmann, T., Vogele, C., Sutterlin, S., Lukito, S., & Kubler, A. (2011). Effects of resting heart rate variability on performance in the P300 brain-computer interface. *International Journal of Psychophysiology, 83*(3), 336-341.

Kelly, S. P., Lalor, E. C., Finucane, C., McDarby, G., & Reilly, R. B. (2005). Visual spatial attention control in an independent brain-computer interface. *IEEE Transactions on Biomedical Engineering, 52*(9), 1588-1596.

Kleih, S., Riccio, A., Mattia, D., Kaiser, V., Friedrich, E., Scherer, R., Müller-Putz, G., Neuper, C., Kübler, A. (2011). Motivation modulates SMR brain-computer interface use. *In proceedings of the 5th International Brain-Computer Interface Conference*, 108-111.

Kleih, S. C., & Kubler, A. (2015). Psychological factors influencing brain-computer interface (BCI) performance. *In Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*, 3192-3196.

Klobassa, D. S., Vaughan, T. M., Brunner, P., Schwartz, N. E., Wolpaw, J. R., Neuper, C., &

Sellers, E. W. (2009). Toward a high-throughput auditory P300-based brain-computer interface. *Clinical Neurophysiology, 120*(7), 1252-1261.

Kollewe, K., Munte, T. F., Samii, A., Dengler, R., Petri, S., & Mohammadi, B. (2011). Patterns of cortical activity differ in ALS patients with limb and/or bulbar involvement depending on motor tasks. *Journal of Neurology, 258*(5), 804-810.

Kubler, A., Furdea, A., Halder, S., Hammer, E. M., Nijboer, F., & Kotchoubey, B. (2009). A brain-computer interface controlled auditory event-related potential (p300) spelling system for locked-in patients. *Annals of the New York Academy of Sciences, 1157*, 90-100.

Kubler, A., Holz, E. M., Sellers, E. W., & Vaughan, T. M. (2015). Toward independent home use of brain-computer interfaces: a decision algorithm for selection of potential end-users. *Archives of Physical Medicine and Rehabilitation, 96*(3), S27-32.

Kübler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J., & Birbaumer, N. (2001). Brain–computer communication: Unlocking the locked in. *Psychological Bulletin, 127*(3), 358-375.

Kübler, A., Nijboer, F., Mellinger, J., Vaughan, T., Pawelzik, H., Schalk, G., . . . Wolpaw, J. (2005). Patients-with-ALS-can-use-sensorimotor-rhythms-to-operate-a-brain-comptuer-interface . *Neurology, 64*(10), 1775-1777.

Liberati, G., Pizzimenti, A., Simione, L., Riccio, A., Schettini, F., Inghilleri, M., . . . Cincotti, F. (2015). Developing brain-computer interfaces from a user-centered perspective: Assessing the needs of persons with amyotrophic lateral sclerosis, caregivers, and professionals. *Applied Ergonomics, 50*, 139-146.

Light, J., & McNaughton, D. (2013). Putting people first: re-thinking the role of technology in augmentative and alternative communication intervention. *Augmentative and Alternative*

Communication, 29(4), 299-309.

Light, J., McNaughton, D., Beukelman, D., Fager, S. K., Fried-Oken, M., Jakobs, T., & Jakobs, E. (2019). Challenges and opportunities in augmentative and alternative communication: Research and technology development to enhance communication and participation for individuals with complex communication needs. *Augmentative and Alternative Communication*, 1-12.

Lin, Z., Zhang, C., Wu, W., & Gao, X. (2007). Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs. I*EEE Transactions on Biomedical Engineering, 53*(12), 2610-2614.

Lopez, M. A., Pomares, H., Pelayo, F., Urquiza, J., & Perez, J. (2009). Evidences of cognitive effects over auditory steady-state responses by means of artificial neural networks and its use in brain–computer interfaces. *Neurocomputing, 72*(16-18), 3617-3623.

Loporto, M., McAllister, C., Williams, J., Hardwick, R., & Holmes, P. (2011). Investigating central mechanisms underlying the effects of action observation and imagery through transcranial magnetic stimulation. *Journal of motor behavior, 43*(5), 361-373.

Lule, D., Diekmann, V., Kassubek, J., Kurt, A., Birbaumer, N., Ludolph, A. C., & Kraft, E. (2007). Cortical plasticity in amyotrophic lateral sclerosis: motor imagery and function. *Neurorehabilation and Neural Repair, 21*(6), 518-526.

Mak, J. N., McFarland, D. J., Vaughan, T. M., McCane, L. M., Tsui, P. Z., Zeitlin, D. J., ... & Wolpaw, J. R. . (2012). EEG correlates of P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis. *Journal of Neural Engineering, 9*(2), 026014.

Mak, J. N., & Wolpaw, J. R. (2009). Clinical Applications of Brain-Computer Interfaces:

Current State and Future Prospects. *IEEE Reviews in Biomedical Engineering, 2*, 187-199.

Marchetti, M., & Priftis, K. (2015). Brain-computer interfaces in amyotrophic lateral sclerosis: A metanalysis. *Clinical Neurophysiology, 126*(6), 1255-1263.

Marinelli, L., Quartarone, A., Hallett, M., Frazzitta, G., & Ghilardi, M. F. (2017). The many facets of motor learning and their relevance for Parkinson's disease. *Clinical Neurophysiology, 128*(7), 1127-1141.

McCane, L. M., Sellers, E. W., McFarland, D. J., Mak, J. N., Carmack, C. S., Zeitlin, D., . . . Vaughan, T. M. (2014). Brain-computer interface (BCI) evaluation in people with amyotrophic lateral sclerosis. *Amyotrophic Lateralal Sclerosis and Frontotemporal Degeneration, 15*(3-4), 207-215.

McCane, L. M., Sellers, E. W., McFarland, D. J., Mak, J. N., Carmack, C. S., Zeitlin, D., ... & Vaughan, T. M. . (2014). Brain-computer interface (BCI) evaluation in people with amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 15*(3-4), 207-215.

McCarthy, J., Light, J., Drager, K., McNaughton, D., Grodzicki, L., Jones, J., . . . Parkin, E. (2006). Re-designing scanning to reduce learning demands: the performance of typically developing 2-year-olds. *Augmentative and Alternative Communication, 22*(4), 269-283.

McCarthy, J. W., & Boster, J. B. (2017). A comparison of the performance of 2.5 to 3.5-year-old children without disabilities using animated and cursor-based scanning in a contextual scene. *Assististive Technology*, 1-8.

McNaughton, D., Giambalvo, F., Kohler, K., Nazareth, G., Caron, J., & Fager, S. (2018). “Augmentative and alternative communication (AAC) will give you a voice”: key

practices in AAC assessment and intervention as described by persons with amyotrophic lateral sclerosis. *In Seminars in Speech and Language, 39*(5), 399-415.

Marchesotti, S., Bassolino, M., Serino, A., Bleuler, H., & Blanke, O. (2016). Quantifying the role of motor imagery in brain-machine interfaces. *Scientific Reports*, *6*, 24076.

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia medica: Biochemia Medica*, *22*(3), 276-282.

Meador, K. J. (1998). Cognitive side effects of medications. *Neurologic clinics, 16*(1), 141-155.

Miner, L., McFarland, D., & Wolpaw, J. (1998). Answering questions with an electroencephalogram-based brain-computer interface. *Archives of Physical Medicine and Rehabilitation, 79*(9), 1029-1033.

Miralles, F., Vargiu, E., Rafael-Palou, X., Solà, M., Dauwalder, S., Guger, C., . . . Daly, J. (2015). Brain–Computer Interfaces on track to home: Results of the evaluation at disabled end-users' homes and lessons learnt. *Frontiers in ICT, 2*.

Moghimi, S., Kushki, A., Marie Guerguerian, A., & Chau, T. (2013). A review of EEG-based brain-computer interfaces as access pathways for individuals with severe disabilities. *Assistive Technology*, *25*(2), 99-110.

Müller-Putz, G. R., Kaiser, V., Solis-Escalante, T., & Pfurtscheller, G. . (2010). Fast set-up asynchronous brain-switch based on detection of foot motor imagery in 1-channel EEG. *Medical & Biological Engineering & Computing, 48*(3), 229-233.

Muller-Putz, G. R., Pokorny, C., Klobassa, D. S., & Horki, P. (2013). A single-switch BCI based on passive and imagined movements: toward restoring communication in minimally conscious patients. *International Journal of Neural Systems, 23*(2), 1250037.

Muller-Putz, G. R., Scherer, R., Brauneis, C., & Pfurtscheller, G. (2005). Steady-state visual

evoked potential (SSVEP)-based communication: impact of harmonic frequency components. *Journal of Neural Engineering, 2*(4), 123-130.

Muthukumaraswamy, S. D. (2013). High-frequency brain activity and muscle artifacts in MEG/EEG: a review and recommendations. *Frontiers in Human Neuroscience, 7*, 138.

Myrden, A., & Chau, T. . (2015). Effects of user mental state on EEG-BCI performance. *Frontiers in Human Neuroscience, 9*, 308.

Neuper, C., Müller, G. R., Kübler, A., Birbaumer, N., & Pfurtscheller, G. (2003). Clinical application of an EEG-based brain–computer interface: a case study in a patient with severe motor impairment. *Clinical Neurophysiology, 114*(3), 399-409.

Neuper, C., Scherer, R., Reiner, M., & Pfurtscheller, G. (2005). Imagery of motor actions: differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG. *Cognitive Brain Research, 25*(3), 668-677.

Neuper, C., Schlögl, A., & Pfurtscheller, G. . (1999). Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor imagery. *Journal of Clinical Neurophysiology, 16*(4), 373-382.

Nijboer, F. (2015). Technology transfer of brain-computer interfaces as assistive technology: barriers and opportunities. *Annals of Physical and Rehabilitation Medicine, 58*(1), 35-38.

Nijboer, F., Birbaumer, N., & Kubler, A. (2010). The influence of psychological state and motivation on brain-computer interface performance in patients with amyotrophic lateral sclerosis - a longitudinal study. *Frontiers in Neuroscience, 4*.

Nijboer, F., Furdea, A., Gunst, I., Mellinger, J., McFarland, D. J., Birbaumer, N., & Kubler, A. (2008). An auditory brain-computer interface (BCI). *Journal of Neuroscience Methods, 167*(1), 43-50.

Nitzan S. Artzi & Oren Shriki (2018) An analysis of the accuracy of the P300 BCI, *Brain-Computer Interfaces*, *5*(4), 112-120,

O'Keefe, B. M., Kozak, N. B., & Schuller, R. . (2007). Research priorities in augmentative and alternative communication as identified by people who use AAC and their facilitators. *Augmentative and Alternative Communication, 23*(1), 89-96.

Obermaier, B., Müller, G. R., & Pfurtscheller, G. (2003). "Virtual keyboard" controlled by spontaneous EEG activity. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,, 11*(4), 422–426.

Oken, B., Memmott, T., Eddy, B., Wiedrick, J., & Fried-Oken, M., (2018). Vigilance state fluctuations and performance using brain–computer interface for communication, *Brain-Computer Interfaces*, 5(4), 146-156.

Oken, B. S., Orhan, U., Roark, B., Erdogmus, D., Fowler, A., Mooney, A., . . . Fried-Oken, M. B. (2014). Brain-computer interface with language model-electroencephalography fusion for locked-in syndrome. *Neurorehabilation and Neural Repair, 28*(4), 387-394.

Oostenveld, R., & Praamstra, P. (2001). The five percent electrode system for high-resolution EEG and ERP measurements. . *Clinical Neurophysiology, 112*(4), 713-719.

Osuagwu, B. A., & Vuckovic, A. (2014). Similarities between explicit and implicit motor imagery in mental rotation of hands: an EEG study. *Neuropsychologia, 65*, 197-210.

Paez-Colasante, X., Figueroa-Romero, C., Sakowski, S. A., Goutman, S. A., & Feldman, E. L. . (2015). Amyotrophic lateral sclerosis: mechanisms and therapeutics in the epigenomic era. *Nature Reviews Neurology, 11*(5), 266-279.

Pasqualotto, E., Matuz, T., Federici, S., Ruf, C. A., Bartl, M., Olivetti Belardinelli, M., . . . Halder, S. (2015). Usability and workload of access technology for people with severe

motor impairment: A comparison of brain-computer interfacing and eye tracking. *Neurorehabilitation and Neural Repair, 29*(10), 950-957.

Peters, B., Higger, M., Quivira, F., Bedrick, S., Dudy, S., Eddy, B., . . . Oken, B. (2018). Effects of simulated visual acuity and ocular motility impairments on SSVEP brain-computer interface performance: an experiment with Shuffle Speller. *Brain-Computer Interfaces, 5*(2-3), 58-72.

Peters, B., Mooney, A., Oken, B., & Fried-Oken, M. (2016). Soliciting BCI user experience feedback from people with severe speech and physical impairments. *Brain-Computer Interfaces, 3*(1), 47-58.

Pfurtscheller, G., & Da Silva, F. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology, 110*(11), 1842-1857.

Phillips, B., & Zhao, H. (1993). Predictors of assistive technology abandoment. *Assistive Technology, 5*(1), 36-45.

Pitt, K., & Brumberg, J. (2018a). Guidelines for Feature Matching Assessment of Brain-Computer Interfaces for Augmentative and Alternative Communication. *American Journal of Speech-Language Pathology, 27*(3), 950-964.

Pitt, K., & Brumberg, J. (2018b). A screening protocol incorporating brain-computer interface feature matching considerations for augmentative and alternative communication. *Assistive Technology*, 1-12.

Pitt, K., Brumberg, J., Burnison, J., Mehta, J., & Juhi, K (in review). *Behind the scenes of non-invasive brain-computer interfaces: A review of electroencephalography signals, how they are recorded, and why they matter.*

Pitt, K., Brumberg, J. & Pitt, A. (in press). Considering Augmentative and Alternative

Communication Research for Brain-Computer Interface Practice. *Assistive Technology Outcomes and Benefits*, *13*.

Plum, F., & Posner, J. B. (1972). The diagnosis of stupor and coma. *Contemporary Neurology Series, 10*, 1-286.

Poujois, A., Schneider, F. C., Faillenot, I., Camdessanché, J. P., Vandenberghe, N., Thomas-Antérion, C., & Antoine, J. C. . (2013). Brain plasticity in the motor network is correlated with disease progression in amyotrophic lateral sclerosis. *Human brain mapping, 34*(10), 2391-2401.

Powers, J. C., Bieliaieva, K., Wu, S., & Nam, C. S. (2015). The human factors and ergonomics of P300-based brain-computer interfaces. *Brain Sciences, 5*(3), 318-356.

Randolph, A., Karmakar, S., & Jackson, M. (2006). Towards Predicting Control of a Brain-Computer Interface. *In Proceedings of the 26th International Conference on Information Systems*, 803-812.

Randolph, A. B., Jackson, M. M., & Karmakar, S. (2010). Individual characteristics and their effect on predicting mu rhythm modulation. *International Journal of Human–Computer Interaction, 27*(1), 24-37.

Ray, J. (2015). Real-life challenges in using augmentative and alternative communication by persons with amyotrophic lateral sclerosis. *Communication Disorders Quarterly, 36*(3), 187-192.

Regan, D. (1989). *Human brain electrophysiology: Evoked potentialsand evoked magnetic fields in science and medicine*. New York: Elsevier.

Rezeika, A., Benda, M., Stawicki, P., Gembler, F., Saboor, A., & Volosyak, I. (2018). Brain-Computer Interface Spellers: A Review. *Brain Sciences, 8*(4), 57

Riccio, A., Simione, L., Schettini, F., Pizzimenti, A., Inghilleri, M., Belardinelli, M. O., . . . Cincotti, F. (2013). Attention and P300-based BCI performance in people with amyotrophic lateral sclerosis. *Frontiers in Humuan Neurosci, 7*, 732.

Rimbert, S., Gayraud, N., Bougrain, L., Clerc, M., & Fleck, S. (2019). Can a subjective questionnaire be used as brain-computer interface performance predictor?. *Frontiers in Human Neuroscience*, *12*, 529.

Romski, M., & Sevcik, R. A. (2018). The complexities of AAC intervention research: emerging trends to consider. *Augmentative and Alternative Communication*, 1-7.

Salameh, J., Brown Jr, R., & Berry, J. (2015). Amyotrophic Lateral Sclerosis: Review. *In Seminars in neurology, 35*(44), 469-476.

Sannelli, C., Vidaurre, C., Müller, K. R., & Blankertz, B. (2019). A large scale screening study with a SMR-based BCI: Categorization of BCI users and differences in their SMR activity. *PloS one*, *14*(1), e0207351.

Scherer, R., Billinger, M., Wagner, J., Schwarz, A., Hettich, D. T., Bolinger, E., . . . Muller-Putz, G. (2015). Thought-based row-column scanning communication board for individuals with cerebral palsy. *Annals of Physical and Rehabilitation Medicine, 58*(1), 14-22.

Seidler, R. D., Bo, J., & Anguera, J. A. (2012). Neurocognitivecontributions to motor skill learning: The role of working memory. *Journal of Motor Behavior, 44*(6), 445–453.

Sellers, E. W., Kubler, A., & Donchin, E. (2006). Brain-computer interface research at the University of South Florida Cognitive Psychophysiology Laboratory: the P300 Speller. *IEEE Transactions on Rehabilitation Engineering, 14*(2), 221-224.

Sellers, E. W., Vaughan, T. M., & Wolpaw, J. R. (2010). A brain-computer interface for long-term independent home use. *Amyotrophic Lateral Sclerosis, 11*(5), 449-455.

Sexton, C. A. (2015). The overlooked potential for social factors to improve effectiveness of brain-computer interfaces. *Frontiers in Systems Neuroscience, 9*, 70.

Shu, X., Chen, S., Yao, L., Sheng, X., Zhang, D., Jiang, N., . . . Zhu, X. (2018). Fast Recognition of BCI-Inefficient Users Using Physiological Features from EEG Signals: A Screening Study of Stroke Patients. *Frontiers in Neuroscience, 12*, 93.

Sigrist, R., Rauter, G., Riener, R., & Wolf, P. (2013). Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychonmic Bulletin and Review, 20*(1), 21-53.

Solis-Escalante, T., Müller-Putz, G., Brunner, C., Kaiser, V., & Pfurtscheller, G. (2010). Analysis of sensorimotor rhythms for the implementation of a brain switch for healthy subjects. *Biomedical Signal Processing and Control, 5*(1), 15-20.

Sprague, S. A., McBee, M. T., & Sellers, E. W. (2016). The effects of working memory on brain-computer interface performance. *Clinical Neurophysiology, 127*(2), 1331-1341.

Stanton, B. R., Williams, V. C., Leigh, P. N., Williams, S. C., Blain, C. R., Giampietro, V. P., & Simmons, A. (2007). Cortical activation during motor imagery is reduced in Amyotrophic Lateral Sclerosis. *Brain Research, 1172*, 145-151.

Stoppel, C. M., Vielhaber, S., Eckart, C., Machts, J., Kaufmann, J., Heinze, H. J., ... & Schoenfeld, M. A. . (2014). Structural and functional hallmarks of amyotrophic lateral sclerosis progression in motor-and memory-related brain regions. *NeuroImage: Clinical, 5*, 277-290.

Sugata, H., Hirata, M., Kageyama, Y., Kishima, H., Sawada, J., & Yoshimine, T. (2016). Relationship between the spatial pattern of P300 and performance of a P300-based brain-computer interface in amyotrophic lateral sclerosis. *Brain-Computer Interfaces, 3*(1), 1-8.

Sutter, E. E. (1992). The brain response interface: communication through visually-induced electrical brain responses. *Journal of Microcomputer Applications,, 15*(1), 31-45.

Thistle, J. J., & Wilkinson, K. M. (2015). Building Evidence-based Practice in AAC Display Design for Young Children: Current Practices and Future Directions. *Augmentative and Alternative Communication, 31*(2), 124-136.

Thompson, D. E., Gruis, K. L., & Huggins, J. E. (2014). A plug-and-play brain-computer interface to operate commercial assistive technology. *Disability and Rehabilitation: Assistive Technology, 9*(2), 144-150.

Thompson, M. C. (2018). Critiquing the Concept of BCI Illiteracy. *Science and Engineering Ethics*, 1-17.

Turner, M. R., Parton, M. J., Shaw, C. E., Leigh, P. N., & Al-Chalabi, A. (2003). Prolonged survival in motor neuron disease: a descriptive study of the King's database 1990–2002. *Journal of Neurology, Neurosurgery & Psychiatry*, *74*(7), 995-997.

Vansteensel, M. J., Pels, E. G. M., Bleichner, M. G., Branco, M. P., Denison, T., Freudenburg, Z. V., . . . Ramsey, N. F. (2016). Fully Implanted Brain-Computer Interface in a Locked-In Patient with ALS. *New England Journal of Medicine, 375*(21), 2060-2066.

Vansteensel., K., Aarnoutse., & Ramsey. (2017). The brain-computer interface researcher's questionnaire: from research to application. *Brain-Computer Interfaces, 4*(4), 236-237.

Vargas-Irwin, C. E., Feldman, J. M., King, B., Simeral, J. D., Sorice, B. L., Oakley, E. M., ... & Donoghue, J. P. (2018). Watch, imagine, attempt: Motor cortex single unit activity reveals context-dependent movement encoding in humans with tetraplegia. *Frontiers in Human Neuroscience*, *12*, 450

Vaughan, T., McFarland, D., Schalk, G., Sarnacki, W., Krusienski, D., Sellers, E., & Wolpaw, J.

(2006). The Wadsworth BCI Research and Development Program: at home with BCI. *IEEE Transactions on Rehabilitation Engineering, 14*(2), 229-233.

Vidaurre, C., & Blankertz, B. (2010). Towards a cure for BCI illiteracy. *Brain Topography, 23*(2), 194-198.

Volosyak, I., Valbuena, D., Luth, T., Malechka, T., & Graser, A. (2011). BCI demographics II: how many (and what kinds of) people can use a high-frequency SSVEP BCI? *IEEE Transactions on Rehabilitation Engineering, 19*(3), 232-239.

Volpato, C., Prats Sedano, M. A., Silvoni, S., Segato, N., Cavinato, M., Merico, A., ... & Birbaumer, N. (2016). Selective attention impairment in amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 17*(3-4), 236-244.

Vuckovic, A., & Osuagwu, B. A. (2013). Using a motor imagery questionnaire to estimate the performance of a Brain-Computer Interface based on object oriented motor imagery. *Clinical Neurophysiology, 124*(8), 1586-1595.

Wander, J., Blakely, T., Miller, K., Weaver, K., Johnson, L., Olson, J., . . . Ojemann, J. (2013). Distributed cortical adaptation during learning of a brain computer interface task. *Proceedings of the National Academy of Sciences, 110*(26), 10818–10823.

Wilkinson, K. M., Light, J., & Drager, K. (2012). Considerations for the composition of visual scene displays: potential contributions of information from visual and cognitive sciences. *Augmentative and Alternative Communication, 28*(3), 137-147.

Witte, M., Kober, S. E., Ninaus, M., Neuper, C., & Wood, G. (2013). Control beliefs can predict the ability to up-regulate sensorimotor rhythm during neurofeedback training. *Frontiers in Human Neuroscience, 7*, 478.

Wolpaw, J., Birbaumer, N., McFarland, D., Pfurtscheller, G., & Vaughan, T. (2002). Brain–

computer interfaces for communication and control. *Clinical Neurophysiology, 113*(6), 767-791.

Wolpaw, J., & McFarland, D. (2004). Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. *In Proceesings of the National Academy of Sciences, 101*(51), 17849-17854.

Wolpaw, J. R., Bedlack, R. S., Reda, D. J., Ringer, R. J., Banks, P. G., Vaughan, T. M., . . . Ruff, R. L. (2018). Independent home use of a brain-computer interface by people with amyotrophic lateral sclerosis. *Neurology*. 91(3), e258-e267.

Wolpaw, J. R., McFarland, D. J., & Vaughan, T. M. (2000). Brain-computer interface research at the Wadsworth Center. *IEEE Transactions on Rehabilitation Engineering, 8*(2), 222-226.

Woolley, S. C. (2014). ALS cognitive behavioral screen manual. San Francisco, CA: The Forbes Norris MDA/ALS Research Center.

Woolley, S. C., & Strong, M. J. (2015). Frontotemporal Dysfunction and Dementia in Amyotrophic Lateral Sclerosis. *Neurologic Clinics, 33*(4), 787-805.

Woolley, S. C., York, M. K., Moore, D. H., Strutt, A. M., Murphy, J., Schulz, P. E., & Katz, J. S. (2010). Detecting frontotemporal dysfunction in ALS: utility of the ALS Cognitive Behavioral Screen (ALS-CBS). *Amyotrophic Lateralal Sclerosis, 11*(3), 303-311.

Zhang, J. Z., Jadavji, Z., Zewdie, E., & Kirton, A. (2019). Evaluating if children can use simple brain computer interfaces. *Frontiers in Human Neuroscience*, *13*, 24.

Zhang, D., Maye, A., Gao, X., Hong, B., Engel, A. K., & Gao, S. (2010). An independent brain–computer interface using covert non-spatial visual selective attention. *Journal of Neural Engineering, 7*(1), 016010.

Zhang, T., Liu, T., Li, F., Li, M., Liu, D., Zhang, R., . . . Xu, P. (2016). Structural and functional

correlates of motor imagery BCI performance: Insights from the patterns of fronto-parietal attention network. *Neuroimage, 134*, 475-485.

Zickler, C., Riccio, A., Leotta, F., Hillian-Tress, S., Halder, S., Holz, E., Staiger-Sälzer, P., Hoogerwerf, E.J., Desideri, L., Mattia, D. and Kübler, A.,. (2011). A brain-computer interface as input channel for a standard assistive technology software. *Clinical EEG and Neuroscience, 42*(4), 236-244.

Appendices

Appendix A: Pre session BCI questionnaire

Date ____ Participant ID: _____ Session Number ____

Please, indicate:

1) Please rate your current level of fatigue and motivation, using the scales below

Fatigue:

Normal		Mild		Moderate		High		Extremely fatigued
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

Motivation:

Extremely **un**motivated		Mildly unmotivated		Neutral		Fairly motivated		Extremely motivated
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

Training Session Number	Date	Fatigue Rating	Motivation Rating	Time since last meal (hours)
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				

Appendix B: Post session questionnaire

- **Fatigue**

1. Following today's copy spelling tasks, indicate your level of fatigue on a scale of 1 – 9, 9 being extremely fatigued, to 1 being NORMAL

Normal		Mild		Moderate		High		Extremely fatigued
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

1a. Post minus pre ratings of fatigue: _____

2. Following today's copy spelling tasks, how satisfied are you with this BCI system?

Very **un**satisfied		Mildly **un**satisfied		Neutral		Mildly satisfied		Very satisfied
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

3. During today's copy spelling tasks, what level of frustration did you experience with using the BCI?

Very **low**		Fairly low		Neutral		Fairly high		Very **high**
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

4. During today's copy spelling tasks, how much <u>physical</u> effort was required to operate the BCI?

Very **low**		Fairly low		Neutral		Fairly high		Very **high**
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

5. During today's copy spelling tasks, how much <u>mental</u> effort or concentration was required to operate the BCI?

Very **low**		Fairly low		Neutral		Fairly high		Very **high**
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

6. Overall how hard did you have to work to complete todays copy spelling tasks?

Very **easy**		Fairly easy		Neutral		Fairly hard		Very **hard**
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

Appendix C: Supplemental Data Tables

Data for pre and post BCI training number scales, time since last meal, and neurophysiological measures (ERS, and ERS-ERD) are provided in the following appendicles for each participant with ALS for each of the 12 BCI sessions.

Pre-Training Measures

Table 1. Pre fatigue

Session	**A1**	**A2**	**A3**	**A4**
1	6	1	4	4
2	3	1	3	3
3	6	1	5	5
4	5	3	4	4
5	5	4	2	2
6	4	1	1	5
7	1	2	4	7
8	4	5	7.5	5
9	3	3	4	4
10	4	2	5	4

11	3	4	3	6
12	1	5	4	6

Table 2. Pre motivation

Session	**A1**	**A2**	**A3**	**A4**
1	9	9	9	8
2	9	9	9	8
3	9	7	9	6
4	9	7	9	7
5	9	8	9	8
6	9	7	9	7
7	9	7	9	6
8	9	7	8	8
9	9	7	8	8
10	9	7	8	8
11	9	7	8	7
12	9	6	8	8

Table 3. Time since last meal (hours)

Session	**A1**	**A2**	**A3**	**A4**
1	3	13	2	1
2	0.33	13	2.5	2
3	0.33	0.75	1.75	1.5
4	0	13	3	2
5	0.5	0.75	3	2
6	0.33	0.41	3	3.5
7	0.5	14	3	1.25
8	0	14	0.83	1.45
9	0	0.75	0.5	2
10	3	16	3	1.5
11	0.5	15	0.33	2
12	3	16	3	1.5

Post Training Measures

Table 4. Post session fatigue

Session	**A1**	**A2**	**A3**	**A4**
1	2	3	6	3
2	2	2	4	3
3	5	1	4	7
4	3	3	5	5
5	5	6	7	4
6	3	3	7	6
7	1	3	4	8
8	3	3	8	7
9	1	4	4	6
10	3	1	5	3
11	2	5	4	5
12	2	5	4	7

Table 5. Fatigue difference

Session	**A1**	**A2**	**A3**	**A4**
1	-4	2	2	-1
2	-1	1	1	0
3	-1	0	-1	2
4	-2	0	1	1
5	0	2	5	2
6	-1	2	6	1
7	0	1	0	1
8	-1	-2	5	2
9	-2	-1	0	2
10	-1	-1	0	-1
11	-1	1	1	-1
12	1	0	0	1

Table 4. Device Satisfaction

Session	**A1**	**A2**	**A3**	**A4**
1	5	8	7	7
2	9	7	3	7
3	7	7	6	6
4	7	9	5	8
5	7	7	6	7
6	8	8	2	9
7	8	8	7	7
8	7	9	3	7
9	8	4	5	6
10	7	5	6	8
11	7	5	4	7
12	8	4	7	8

Table 5. Frustration with BCI control

Session	**A1**	**A2**	**A3**	**A4**
1	2	6	6	7
2	2	6	6	5
3	4	5	7	6
4	5	5	4	3
5	4	6	7	5
6	5	3	8	2
7	2	3	5	2
8	5	2	6	6
9	3	7	7	6
10	3	6	5	2
11	1	6	7	3
12	3	8	5	3

Table 6. Physical effort

Session	**A1**	**A2**	**A3**	**A4**
1	1	5	1	2
2	1	5	3	2
3	2	2	6	3
4	3	3	7	2
5	1	5	6	2
6	1	6	6	1
7	1	3	5	2
8	1	3	5	3
9	1	6	5	3
10	2	3	5	3
11	2	6	5	2
12	1	4	7	2

Table 7. Mental effort

Session	**A1**	**A2**	**A3**	**A4**
1	7	8	8	6
2	7	8	9	4
3	8	7	9	4
4	6	7	8	7
5	7	7	8	4
6	3	8	6	6
7	5	6	6	1
8	6	4	5	4
9	7	7	6	7
10	7	6	6	7
11	6	8	6	7
12	5	7	7	5

Table 9. Overall hardness

Session	**A1**	**A2**	**A3**	**A4**
1	8	7	6	3
2	4	7	9	2
3	3	6	7	5
4	5	7	7	4
5	2	7	8	2
6	6	7	6	3
7	5	4	6	2
8	5	4	4	5
9	5	7	6	6
10	2	4	6	3
11	4	7	6	3
12	6	7	7	3

Neurophysiological Measures

Table 10. Peak ERS (microvolts^2) for left sided electrode locations; C3 for A1, A2, and A3, and C3 (session 1), and C1 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	0.726	0.095	0.048	0.056
2	0.184	0.5	1.076	0.103
3	0.802	0.052	0.402	0.049
4	0.449	0.231	0.251	0.044
5	0.274	0.23	1.14	0.077
6	0.186	0.419	1.892	0.067
7	0.25	0.107	0.16	0.076
8	0.156	0.111	0.049	1.359
9	0.378	0.033	0.321	0.06
10	0.254	0.068	0.762	0.087
11	0.219	0.342	0.063	0.066
12	0.377	0.058	0.078	0.059

Table 11. Peak ERS (microvolts^2) for right sided electrode locations; C4 for A1, A2, and A3, and C4 (session 1), and C2 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	0.596	0.105	0.144	0.053
2	0.18	0.54	1.274	0.17
3	0.813	0.09	0.44	0.072
4	1.079	0.612	0.277	0.041
5	0.871	0.381	1.375	0.06
6	0.302	0.383	1.539	0.055
7	0.368	0.132	0.159	0.095
8	0.183	0.18	0.075	1.385
9	0.452	0.033	0.292	0.065
10	0.386	0.146	0.868	0.101
11	0.218	0.593	0.074	0.063
12	0.262	0.119	0.082	0.053

Table 12. Peak ERS – noise (microvolts^2) for left sided electrode locations; C3 for A1, A2, and A3, and C3 (session 1), and C1 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	0.532	0.061	0.039	0.041
2	0.017	0.036	0.955	0.003
3	0.4	0.033	0.26	0.023
4	0.226	0.166	0.136	0.03
5	0.07	0.157	0.942	0.041
6	0.154	0.395	0.89	0.036
7	0.22	0.083	0.089	0.035
8	0.131	0.061	0.034	0.449
9	0.298	0.017	0.236	0.034
10	0.004	0.032	0.601	0.053
11	0.135	0.29	0.048	0.031
12	0	0.04	0.059	0.04

Table 13. Peak ERS – noise (microvolts^2) for right sided electrode locations; C4 for A1, A2, and A3, and C4 (session 1), and C2 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	0.473	0.069	0.128	0.033
2	0.051	0.028	1.004	0.031
3	0.578	0.057	0.337	0.043
4	0.839	0.51	0.145	0.028
5	0.036	0.296	1.014	0.032
6	0.2	0.34	0.554	0.031
7	0.344	0.1	0.082	0.058
8	0.152	0.088	0.042	0.627
9	0.316	0.019	0.248	0.03
10	0.13	0.085	0.782	0.057
11	0.172	0.515	0.059	0.034
12	0.168	0.101	0.061	0.031

Table 14. Peak ERS – ERD (microvolts^2) for left sided electrode locations; C3 for A1, A2, and A3, and C3 (session 1), and C1 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	0.254	0.011	-0.004	-0.007
2	0.028	-0.01	-0.179	-0.063
3	0.143	-0.006	0.054	-0.13
4	0.171	0.063	-0.001	0.002
5	0.109	0.127	-0.183	0.001
6	0.045	0.046	0.496	0.027
7	0.044	-0.088	-0.001	0.025
8	0.041	0.018	-0.001	0.207
9	0.054	0.007	0.094	0.018
10	-0.094	0.019	-0.028	-0.035
11	0.054	-0.234	0.013	0.023
12	0.068	0.015	0.021	0.002

Table 15. Peak ERS – ERD (microvolts^2) for right sided electrode locations; C4 for A1, A2, and A3, and C4 (session 1), and C2 (sessions 2-12) for A4 as they utilized the lower limb for BCI control during sessions 2-12.

Session	**A1**	**A2**	**A3**	**A4**
1	-0.01	-0.008	-0.076	-0.004
2	-0.003	0.002	0.024	0.042
3	0.109	0.031	-0.043	0.011
4	0.394	-0.071	-0.051	-0.001
5	0.535	0.136	0.042	-0.011
6	0.128	-0.231	-0.041	0.013
7	0.173	0.035	-0.03	0.04
8	0.073	-0.047	0.014	-0.105
9	0.047	0.009	0.123	-0.012
10	0.056	0.061	0.051	-0.002
11	0.03	0.142	-0.002	0.015
12	0.08	0.011	0.004	-0.019

Appendix D: The BCI Screener by Pitt & Brumberg (2018b)

A Screening Protocol Incorporating Brain-Computer Interface Feature Matching Considerations for Augmentative and Alternative Communication

Kevin Pitt., CCC-SLP & Jonathan Brumberg., PhD.

Instructions on this form may be abbreviated. See manual for full guidelines.
Please record use of medications on a separate sheet.

Today's date
Given by (clinician): **Start time: _____** **End time: _____**

Introductory Information:

*Participant currently using mechanical ventilation? **Y / N** *Likely remaining with ventilation? **Y / N**
Primary Communication method:

Current AAC method, if applicable:

Communicational method used for screening protocol responses:

Diagnosis, and date of diagnosis: Date and region of symptom onset:

Date of last hearing test (pass/fail): Date of last vision test (pass/fail):

1) Handedness:
Do/did you primarily use your right / left hand to?
If applicable, prior to paralysis. If they have never been able to perform the selected actions due to congenital motor impairments, please individualize actions (see manual for examples) and record below. Select 'uncertain' if handedness cannot be ascertained.

1A) Throw a ball _Right hand _Left hand _Both hands equally well
1B) Draw _Right hand _Left hand _Both hands equally well
1C) Clarification: The subject is: _Right handed _ Left handed _Uses both hands _Uncertain

Modified task 1A: Modified task 1B:

---

2) History of Seizures:
2A) *Have you ever had a seizure?* **_ Yes _No**
If yes, please provide history in the general considerations section.

3) Vision:
3A) Four Corners. *Communicate whenever you seen an item appear.*
__Center __Right upper quadrant __Left lower quadrant __Right lower quadrant __ Blank

__Left upper quadrant __Unable to complete due to severe visual impairment
Score 1 point per correct response Enter score /6

3B) *Do you use contact lenses or glasses?* **_ Yes _No**
3C) *Do you have trouble seeing far away?* **_ Yes _No**
3D) *Do you have any other difficulties with your vision?* **_ Yes _No** (if yes, provide details as possible)

4) Hearing:
4A) *Do you use hearing amplification?* **_ Yes _No**
4B) *Do you have difficulty hearing in background noise (e.g., in a restaurant)?* **_ Yes _No**
4C) *Do you have any other difficulties with your hearing?* **_ Yes _No** (if yes, provide details as possible)

---

5) Literacy:
5A*) Are you able to read?* **_ Yes _No**. If no, *were you able to read in the past?* **_ Yes _No**
5B) Participant is to read/perform "*Look Up*" (see manual for stimuli and adapt to meet individual's voluntary motor, and visual capabilities as necessary)
_Accurate _Inaccurate _Unable to complete due to severe visual impairment

5C) *I will present a familiar object and ask you some questions about how to spell the word.*
Is the first letter c? **_ Yes _No**
Is the second letter o? **_ Yes _No**
Is the third letter r? **_ Yes _No**
Is the fourth letter m? **_ Yes _No**

_____
6) Fatigue: Use visual scale in provided in the manual
6A) *I want you to indicate your **current** level of fatigue on a scale of 1 to 4, with 1 being not fatigued, to 4 being severely fatigued*: ____

6B) *I want you to indicate your **average** level of fatigue (e.g., over the past 2 weeks) on a scale of 1 to 4, with 1 being not fatigued, to 4 being severely fatigued*: ____

_____
7) Pain:
7A) *Have you been in consistent pain over the past two weeks*? **_ Yes _No** <u>If no, skip to section 7D</u>

If yes*, I am going to ask you questions about your <u>average</u> level of pain (e.g., over the past two weeks). Communicate your answer using a scale of 1 (never or rarely interferes) to 4 (always interferes).*

7B) *At what level does your average level of pain interfere with your ability to learn new tasks?* _____

7C) *At what level does your average level of pain interfere with your ability to think (e.g., remember things, concentrate)?* _____

7D) *Are you currently in pain?* **_ Yes _No** If no, skip to section 8

If yes, *I am going to ask you questions about your current level of pain. Communicate your answer using a scale of 1 (never or rarely interferes) to 4 (always interferes).*
7E) *At what level does your current level of pain interfere with your ability to think (e.g., remember things, concentrate)?* _____

---

8) Comprehension & Orientation
I am going to ask you some more yes and no questions

8A) *Is your last name Smith?* (should be incorrect)	**_ Yes _No**
8B) *Are you _____ years old?* (should be correct)	**_ Yes _No**
8C) *Is your name _____?* (should be correct)	**_ Yes _No**
8D) *Is this a hotel_____?* (should be incorrect)	**_ Yes _No**
8E) *Is this _____?* (should be correct)	**_ Yes _No**
8F) *Do you live in Toronto?* (should be incorrect)	**_ Yes _No**
8G) *Do you live in _____?* (should be correct)	**_ Yes _No**
8H) *Is this month _____ ?*(should be correct)	**_ Yes _No**
8I) *Is this month _____ ?(*should be incorrect, 1 month prior)	**_ Yes _No**
8J) *Is this a restaurant?* (should be incorrect)	**_ Yes _No**
8K) *Does March come before June?* (correct)	**_ Yes _No**
8L) *Do you eat a banana before you peel it?* (incorrect)	**_ Yes _No**

Score 6 points (12 corr), 5 (11 corr), 4 (10 corr), 3 (9 corr), 2 (8 corr), 1 (7 corr), else score 0

Enter score /6

---

9) Following Directions (Adapt to meet individual's voluntary motor capabilities as required).

9A) 1 step direction: *Look up* **_ Accurate _Inaccurate**
/2
9B) 2 step direction: *Blink, look up* **_ Accurate _Inaccurate**
/2
9C) 3 step direction: *Look down, move your finger, look up* **_ Accurate _Inaccurate**
/2
Note any adaptions or task difficulties:

Score 2 points for each set of directions performed correctly, else score 0

Total Score /6

---

10) Motor Imagery (MI)

10A) **Default Preference** for First-Person/Kinesthetic versus Third-Person/Visual Motor Imagery. After participant has performed tasks via motor imagery, ask in the order presented which modality was used.

1A	Tapping foot:	__ First person (kinesthetic)	__Third person (visual)
1B	Making a fist:	__ Third person (visual)	__ First person (kinesthetic)
2A	Curling Toes:	__Third person (visual)	__ First person (kinesthetic)
2B	Tapping your finger:	__ First person (kinesthetic)	__Third person (visual)

3) *Generally, is it more natural for you to use first person imagery during all these tasks?*
__Yes __No

10B) **Hand Rotation** (See manual for a scoring modification if the participant cannot complete this task due to a sensory impairment). **Right/left** (below) denotes the laterality of the presented hand. **Yes/No** denotes the correct binary answer.

I will ask you if the picture is of a right or left hand
- Practice: Right (yes)
Are you ready to continue? *I will ask you if the picture is of a right or left hand.*

- Experimental: Left (no), Left (yes), Right (yes), Left (yes), Right (yes), Right (no), Left (no), Right (no)
Score 5 points (8 corr), 4 (7 corr), 3 (6 corr), 2 (5 corr), else score 0 Enter score /5

10C) **Self-Rating of First-Person Imagery**
After demonstrating a movement overtly (sitting position), the participant is to perform all tasks via first-person (kinesthetic) motor imagery. As possible, a physical practice should precede imagery performance. Use the corresponding 5-point number scale (1 = no sensation, to 5 = as intense as executing the action) for scoring. If the participant has never been able to perform a task physically due to congenital paralysis, interpret results with caution.

	Imagery rating:	
1) Making a fist:	Overt	Time since physical task performance:
2) Foot tapping:	Overt:	Time since physical task performance:
3) Thumb to index finger tapping:	Overt:	Time since physical task performance:
4) Wiggling toes:	Overt:	Time since physical task performance:
5) _____	Overt:	Time since physical task performance:

(Note individualized task used for item 5)

Mean imagery rating /5

10D) **Object Rotation** (See manual for a scoring modification if the participant cannot complete this task due to a sensory impairment).

Red/black below denotes the correct tip of thumb location. **Yes/No** denotes the correct binary answer.
*I will ask you if the **TIP** of your thumb is resting on the **red or black** part of the handle.*
- Practice: Red (yes) *Are you ready to continue*?

- Experimental: Black (no), Black (yes), Red (yes), Red (no), Red (yes), Black (yes)
Score 5 points (6 corr), 4 (5 corr), else score 0 Enter score /5

NOTE: If the participant could not complete rotation tasks due to a visual impairment then multiply the mean imagery rating by 3, and do not score any other tasks in the motor imagery section.

Enter score /15

---

11) Attention / Working Memory
11A) Experiential: *Pay attention, I will ask you how many times the "ice cream" was presented.*

A) Was the ice cream presented four times? **_ Yes _No**
B) Was the ice cream presented five times? **_ Yes _No**
Score 2 if the response to only question B was YES, else score 0 Enter score /2

11B) *You will see and/or hear numbers and objects. Pay attention, at the end of the sequence I will ask you if the number one and/or the cookie was presented.*

A) Was the number one presented? **_ Yes _No**
B) Was the cookie presented? **_ Yes _No**
Score 1 point per correct response, A= yes, B= no Enter score /2

11C) If the participant has a severe visual or hearing impairment please see the manual for task modifications.

You will see different objects on the screen and at the same time hear different numbers. Pay attention, at the end of the sequence I will ask you about whether you saw the cheese and/or heard the number 5.
- Experimental: Fires (1), Hotdog (3), Fries (5) ^{*A}, Hotdog (2), Popcorn (3), Hotdog (2), Popcorn (1), Cheese (2)^{*v}**,** Popcorn (3), Fires (2).

A) Did you hear the number 5 (or feel left side tap for hearing modification)? **_ Yes _No**
B) Was the cheese presented (or feel left side tap for visual modification)? **_ Yes _No**
Score 1 point per correct response, A & B both = yes Enter score /2

---

12) Cognitive Motor Learning / Abstract Problem Solving
12A) **Circle/square** below denotes the shape presented. **Yes/No** denotes the correct binary answer. **X** denotes no answer required.

Is the shape the same as the one shown two turns back?
- Practice: Triangle (X), Circle (X), Triangle (yes) *Continue?*
- Experimental: Circle (X), Triangle (X), Circle (yes), Triangle (yes), Triangle (no), Circle (no)

Score 3 points (4 corr), 2 (3 corr), else score 0 Enter score /3

12B) *Which of the following three options best describes how **GLOVES & SCARVES** are alike?*
1. Made of leather (incorrect) 2. Winter clothing (correct) 3. Both worn near the head (incorrect)

Score 0 if incorrect, 3 if correct. Enter score /3

---

13) Motivation for BCI use:
13A) *I want you to indicate your level of motivation to use a brain-computer interface for communication using a scale of 1 – 4, with 1 being unmotivated to, 4 highly motivated.:*

13B) *I want you to indicate how helpful you think brain-computer interfaces will be for communication in your daily life, on a scale of 1 – 4 with 1 unhelpful to 4, very helpful:*

_____

Enter score /8

14) Comfort with Computers:
14A) *I want you to indicate on a scale of 1 – 4, your comfort level with using computers, with 1 being computers are very difficult to use to 4, very easy to use:* _____

---

15) Motor functionality: In relation to brain-computer interface use, a screening of voluntary motor control including the: upper and lower limbs, face, tongue, horizontal/vertical eye movement, presence of uncontrolled, or impulsive movements, and posture should be completed. Describe findings below, continuing on a separate page if needed. See manual for further guidance of motor assessment.

15A) **Oculomotor movement**, describe findings including; vertical and lateral range of motion, pursuit (following an object/finger), speed, effort, stability), and reliability (reproducibility of task). Score 1 point for each direction which they demonstrate a full range of stable oculomotor movement (up, down, left and right).

Enter score /4

15B) **Facial, and tongue movements,** describe findings including; range of motion, speed, effort, stability (e.g., tremor), and reliability (reproducibility of task).

15C) **Upper, lower limb, and trunk** motor function, describe findings including; range of motion, speed, effort, stability (e.g. tremor), and reliability (reproducibility of task).

15D) **Posture/ positioning for device access**, describe findings including; areas where the headrest may compress the electroencephalography (EEG) cap (as applicable), and how the participant may be most comfortable, and be afforded best access to the device.

Is there a concern for the participants' reliability to provide an accurate self-report?

Yes (provide details below) ____ No____ Unable to ascertain (provide details below) ____

Concern may be based on, but is not limited to; clinical observations, unclear responses to self-report-based tasks (e.g., an unclear self-report for explicit imagery ratings), and caregiver input.

Total Screening Scores

Practice items are not included in scoring.

Level of Current Fatigue	/4	Oculomotor:	/4
Level of Average Fatigue	/4	Visual Acuity	/6
Mean KI score (generic tasks #1-4)	/5	Comfort with Tech.	/4
KI score for individualized task #5	/5	Motivation for BCI	/8
		Cognitive	/24

Check if participant was NOT able to complete rotation imagery tasks:
Motor Imagery: /15

Was the individual currently in pain (**Yes / No**) and/or have habitual pain (**Yes / No**)?

Does the individual have a history of seizures? **_ Yes _No**

Is the self-rating for the individualized explicit imagery task higher than the mean of the four other generic tasks? **_ Yes _No**

Self-Report Details, General Considerations & Medications.

If the information has not been provided by the caregiver (see caregiver questionnaire), a list of primary medications (especially: sedative, anti-depressant, anti-epileptic, psychiatric or pain medications) should be noted. Please discuss any difficulties in completing tasks, strengths and weaknesses noted during performance of protocol tasks, etc. Continue on a separate page if needed.