A Comparison of Movement-Related Cortical Potentials and Their Application in Brain-Computer Interfaces for Autism Spectrum Disorder

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Brain-computer interfaces have the potential to improve the lives of many populations who benefit from neurofeedback. Autism Spectrum Disorder is a condition experienced by many and its deficits are potentially improved for some using brain-computer interface technology. Various techniques have already been used to illustrate improvements in ASD across different brain signals and interactive interfaces. In particular, movement-related cortical potentials are related to executive functioning of movement and have been shown to be successful in other systems. This thesis investigates the effect of Autism Spectrum Disorder in adults on how movement-related cortical potentials are elicited in the brain compared to neurotypical populations to determine whether the motor systems that elicit such signals are abnormally functioning, and as a result whether they may be improved with neurofeedback.

In addition to understanding the EEG response for people with ASD to brain-computer interfaces, it is important to gain insights into their perception of such technologies. This thesis also examines how people with ASD perceive different potential brain-computer interfaces. Quantitative and qualitative data was collected and analysed across three different interfaces (auditory, visual, and haptic) and two different tasks (real movement and imagined movement execution).

The EEG results show statistically significant differences in the elicitation of movement-related cortical potentials (MRCPs) between the autistic and neurotypical group, thus indicating possible underlying abnormalities in the motor systems being activated. The features of MRCP were much smaller in amplitude in the ASD group, suggesting that fewer neurons are being recruited for movement-based actions. Since other studies have demonstrated success when

improving MRCPs in populations suffering from Parkinson's and stroke, it is thus inferred that such neurofeedback may also benefit those with Autism Spectrum Disorder.

While there were no statistical differences regarding EEG-related performance for different modalities, qualitative results suggest common themes regarding people with ASD's subjective perceptions, including the need for feedback on performance and strong preferences for different types of modalities. These results emphasize the importance of considering both quantitative and qualitative data when designing brain-computer interfaces for these populations. This research demonstrates an opportunity to use MRCP-based neurofeedback to help populations with ASD, as well as emphasizes the importance and insights of capturing qualitative data in the process.

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List of Abbreviations

ASD	Autism Spectrum Disorder
EEG	Electroencephalogram
ECoG	Electrocorticography
MNS	Mirror Neuron System
ERP	Event-Related Potential
VEP	Visual Evoked Potential
AEP	Auditory Evoked Potential
SEP	Somatosensory Evoked Potential
MRCP	Movement-Related Cortical Potential
BCI	Brain-Computer Interface
ADHD	Attention-Deficit Hyperactive Disorder
LPP	Locality-Preserved Projections
NS1	Negative Slope 1
NS2	Negative Slope 2
PA	Peak Amplitude of Negativity
RR	Rebound Rate
SNR	Signal-to-Noise Ratio
EMG	Electromyography
ANOVA	Analysis of Variance
LMM	Linear Mixed Models

1. Background

1.1 Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) is the general term for a family of neurodevelopmental disorders that are characterized by deficits in communication, social understandings, unpredictable sensitivity to various external stimuli, and unusual behaviours [1]. ASD is a lifelong condition that is usually diagnosed in children when they are about three years of age, but can occur at any point in their life [2]. Currently, a diagnosis is based on an individual's results on the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) criteria outlined by the American Psychiatric Association [3]. The severity of the diagnosis is categorized as high-functioning, moderately-functioning, and low-functioning ASD. The classification of high to low-functioning autism was made by the Austrian pediatrician Hans Asperger, in an effort to spare the lives of children with ASD, who were persecuted by the Nazi party for being 'neurologically inferior' [4]. Thus, the term *high-functioning ASD* is also known as Asperger's syndrome. The population without ASD is often described as 'neurotypical,' thus this term will be used therefor.

Of particular interest in ASD research is people with ASD's hypersensitivity to external stimuli. Historically, it has been nearly impossible to predict what type of stimuli a particular autistic individual will be oversensitive to, as well as what type of stimuli the individual may favour [5]. Many studies have aimed to identify the origin and preferences of these sensitivities. One study attempted to explain the interaction between stimuli preference and performance between autistic children and neurotypical children (N=87, 17 of which belonged to the autistic group) [6]. In this study, both groups of children were asked to press a key in response to one of

three cues: auditory, visual, and haptic. Performance was measured via response time. In both groups, children had the lowest response time using auditory cues, and had the highest with tactile cues. It was noted that both groups reported similar preferences to auditory and visual stimuli, however the researchers pointed out some factors that might have skewed results. For example, the tactile stimulation that was a touch by the experimenter might have negatively affected children that avoid social interaction, which is a common observation in people with ASD. Furthermore, the researchers propose that the deficiencies in performance via response times with children in the ASD group may have been due to learning disturbances, rather than a deficit in the cognitive processing of sensory inputs. While research exists examining hypersensitivities, there is little research available in examining how they may impact BCIs [7]. Thus, there is still more research needed that can control these factors to determine if different external stimuli elicit different responses in BCIs designed for people with ASD.

Due to the variance in sensitivities prevalent with ASD, it has been difficult to find an explanation or trend in what type of stimuli will be hypersensitive for ASD population. These sensitivities are believed by some researchers to be caused by abnormalities in sub-systems of the nervous system that are responsible for processing stimuli. A popular area of research aims to assist individuals with ASD in tolerating these external stimuli, known as sensory integration therapy [5][8]. The most notable example of this research is Temple Grandin's famous 'hugging machine,' in which touch pressure is applied in a hugging fashion to help develop a tolerance to touching, as well as reduce anxiety and nervousness in the participant [9]. Her research has been very impactful due to the success of her device, as well as her own diagnosis of high-functioning ASD. The 'insider experience' she has on how stimuli are perceived show how valuable it is to have designers of these systems work with those with ASD to make sure that the systems will be

successful in real-world use. Such research has supported the "nothing about us without us" slogan, which describes the importance of including the affected group as part of the decision-making and design process in order to properly address the needs of that group [10]. This slogan is often heard in ASD communities and is important to find new ways to make individuals with ASD as comfortable as possible while participating in day-to-day activities with others.

Paired with their deficits in social skills, it can be difficult for adults with ASD to cope with simple tasks such as having a conversation or making a phone call. Social skills are a vital part in carrying out these tasks in a manner accepted by society. Social skills are currently addressed in behavioural and speech therapy, in which children with autism are taught how to communicate thoughts and feelings in a socially acceptable manner. These sessions involve several trained experts and are often expensive, so it is imperative for the families of those with ASD to have a supplement or alternative to reduce the frequency of these sessions. Researchers predict that an inability to develop social skills stems from an inability to imitate behaviours and actions in others [11]. It is theorized that the ability to imitate the actions of behaviours is mediated by the mirror neuron system (MNS), which is described in further detail in section 1.2. It is believed that ASD can be quantitatively described via abnormal representations of the MNS [11].

While the severity of these deficits varies significantly between individuals, many people with ASD report having difficulty performing movements involving complex coordination such as writing and hopping on one foot [12]. Some research exists that may support this observation in the brain. For example, one study found that children with autism have an increase in white brain matter around the primary motor cortex which is associated with functional movement impairment [13]. This has been linked to abnormal observations in research studies examining the motor systems at play. It should also be noted that the cognitive resources responsible for planning

and performing these movements are also involved in the MNS. Thus, abnormalities in MNS may also explain the deficits of fine motor control and executive functioning in those with ASD. Researchers are currently unsure of what exactly would cause this abnormal MNS in the ASD population. It should be noted that the mirror neuron system is still a hypothesis at this point, and some researchers think that an abnormal MNS in ASD is a consequence of some other factor such as poor attentional engagement in studies, and difficulties in fine motor movements or visual processing [14].

Society is impacted positively when autistic people are able to participate in society. Many influential people, such as screenwriter Dan Aykroyd, and creator of the popular children's franchise *Pokémon* Satoshi Tajiri, are clinically diagnosed with ASD. Furthermore, people with ASD will improve in their quality of life when they are able to communicate effectively to solve problems and form relationships with others. Thus, there are benefits in the well-being of the community as well as in industry. Researchers are actively looking for new ways to engage people with ASD more in society, and to find new ways to help them contribute to their communities. Therefore, we should value their contributions to society, and continue our research into finding the best ways to help them successfully interact with the rest of the population. One such opportunity to facilitate this is by using brain-computer interfaces to teach positive cognitive behaviours and facilitate communication and control for ASD.

1.2 Electroencephalography

Many studies investigating the underlying cognitive systems of ASD population use electroencephalography (EEG) to capture and represent the electrical activity of the brain. Using electrodes and gel at the scalp surface, the aggregated neuronal activity of the brain is recorded as voltage fluctuations [15], [16]. When large groups of neurons activate in unison, the potentials in the EEG signal fluctuate [17]. In some cases, neuroscience has analyzed the morphology and patterns associated with these fluctuations and how they correspond to the biophysical processes happening within the brain. For example, when an individual wishes to execute a motor task, neurons are recruited by synchronizing the activities of these synapses between groups of neurons. These firings are forms efferent volley and eventually activate muscle cells at the end of the motor chain of the neuromuscular pathway, which will then perform the task the user intends to do.

The fundamentals of electric activities from the brain was first proposed by Richard Caton in 1875, who first described such an phenomenon from the brains of rabbits and monkeys [18]. His short excerpt described the electrical activity in the brain, but did not discover any more details. In 1890, a Polish physiologist named Adolf Beck was the first to discover oscillations and patterns in the brain's electrical potentials, and in particular their changes to a variety of sensory stimulations [19]. Several researchers began experimenting with these electrical activities in animals, but it wasn't until 1924 when the first human EEG was recorded by Hans Berger [20]. It wasn't until 1929 that the first research journal article published his work on EEG [21].

At the infancy of this area of research, the procedures of acquiring these electric signals were rather invasive, as electrodes and other instruments were either directly inserted inside the brain or on the surface of the brain, under the skull and scalp [3][6]. These recording methods were

rather rudimentary, and a formal procedure of acquisition was not formalized until the late 1940s-1950s by Wilder Penfield and Herbert Jasper [22][23]. Their process is known as electrocorticography (ECoG), and uses electrodes placed in a grid-like array placed directly on the surface of the brain to record electrical activity. ECoG is beneficial in recording brain potentials that require higher spatial resolution, however it is an invasive process that requires surgery to implant the electrodes.

With non-invasive EEG, electrodes are painlessly and safely secured to the surface of the scalp and the brain's electric activity is recorded through the surface layers of brain matter, the skull, and the skin. The locations for placing the electrodes are standardized in a configuration known as the 10-20 system, where electrode location are proportionate to 10 or 20 percent of the length from the individual's anion to inion [24]. FIGURE 1 illustrates the International 10-20 system for EEG recording.

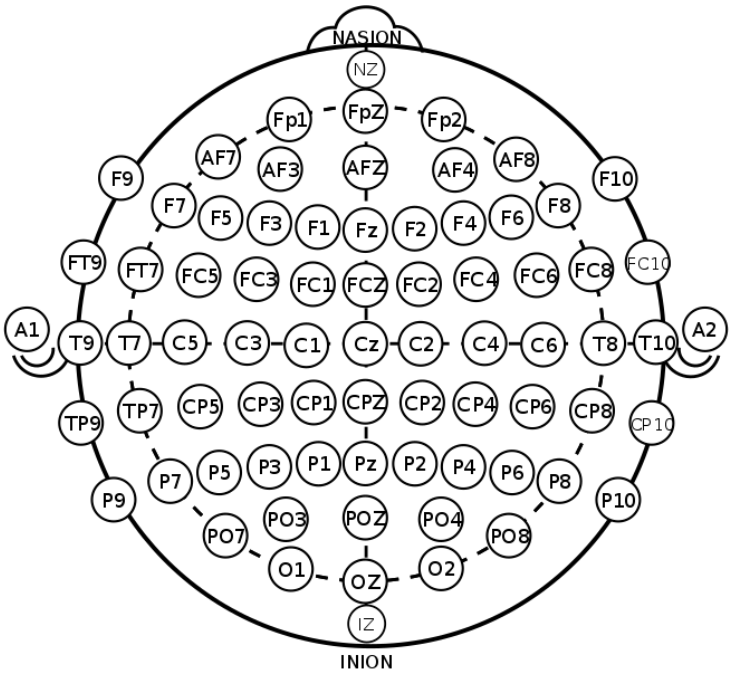


FIGURE 1 The standardized layout of the International 10-20 system for EEG recording. Each letter stands for the region of the brain the electrodes are located on, and the number indicates the position laterally (Fp = Pre-frontal, F = Frontal, C = Central, T = Temporal, P = Parietal, and O = Occipital). (Figure reproduced from [85], which is available under CC0 1.0 Universal (CC0 1.0) Public Domain Dedication license).

Compared to invasive methods for acquiring EEG, non-invasive methods are more likely to be adopted into commercial devices because they do not require introducing implants into the body. However, drawbacks exist that make non-invasive EEG problematic for commercial devices. The most prevalent issues are that non-invasive EEG has low spatial resolution, is prone to noise, and cannot measure activities of deeper brain structures [25]. Despite theses limitations, non-invasive methods are the most likely modality for non-clinical commercial products in the foreseeable future.

The analysis of EEG signals is an extensive area of research. There are numerous ways to extract more informative components from EEG signals. Depending on the purpose of the analysis, one can identify several parts of EEG that can correspond to an individual's intentions or desired action. These components of EEG are grouped into two main occurrences in EEG signals: rhythmic activities and event-related potentials. Rhythmic activities are periodic components in the EEG that correspond to various aspects of perception and cognition, such as attention, consciousness, and memory functions [26]. There are several types that occur at different frequencies and different locations on the brain. Of particular interest to autism research are neural oscillations pertaining to the MNS because of the role it plays in early cognitive development. Mirror neurons are a class of neuron that becomes active while performing actions, or while observing someone else performing a similar action [27]. It was proposed that the cortical activation caused by mirror neurons has a critical role in understanding and imitating the behavior of others [28]. It has been theorized that these mirror neurons are working abnormally in people with ASD, which could explain their difficulties in learning social skills [29]. The main cortical representation of the MNS is quantified in EEG recordings as *mu* rhythms, which are found in the 8-12 Hz frequency range over the primary motor cortex and have long been associated with the

cortical processing of movements [30]. The decreases/increases in these rhythms can be identified prior and after the onset of movement [31].

Event-related potentials (ERPs) are changes in the EEG signal that are triggered by some event or stimuli. Compared to rhythmic activities, which can have ongoing periodic changes, ERPs will have a single, non-periodic change in voltage related to a specific event. There are many different types of ERPs each characterized by their time of occurrence or shape in the EEG, or the nature of the event that causes it [32]. In particular, there are three ERPs that are often mentioned in the autism neuroscience literature: P300s, steady-state evoked potentials, and movement-related cortical potentials (MRCPs).

The P300 wave is elicited with decision-making and natural response to a novel stimulus and are strongest over the parietal area of the brain. The P300 presents itself as a positive increase in voltage approximately 300 ms after the triggering stimuli is presented. The P300 is beneficial in many systems because of its consistency in its waveform structure and its presence in every person. The only thing that may change is the voltage amplitude, which will vary depending on factors such as age and the intensity of stimuli [33].

Steady-state evoked potentials are repetitive event responses, that are carried out by a stimulus being applied at the same frequency as the stimulus being applied [34]. This is an umbrella term that can incorporate one of more types of evoked potentials, such as visual evoked potentials (VEPs), auditory evoked potentials (AEPs), and somatosensory evoked potentials (SEPs). VEPs are evoked in response to a bright stimulus (such as flashes) that appears in the person's gaze, AEPs are evoked with an auditory stimulus, and SEPs are evoked in response to a

tactile stimulus (such as touch or vibrations) [15]. When applied in a steady-state manner, these potentials will take a periodic waveform that will cycle at the same frequency as the stimulus.

Different from the above two ERPs, which are induced by external stimulus, movement-related cortical potentials (MRCPs) are a type of slow cortical potential that is generated prior to voluntary movement by an individual, either spontaneously or in response to a warning cue [35]. As such, it is a spontaneously generated signal by the brain, not relying any external stimuli. The MRCP will be evoked in the area of the motor cortex responsible for motor function of that limb. For example, upon dorsiflexion of either foot an MRCP will be generated at the center of the motor cortex, about the electrode Cz indicated on FIGURE 1. MRCPs consist of a slow negative potential prior to movement, followed by a rebound back to the baseline after movement execution. In spontaneous movements, the negative component is known as the Bereitschaftspotential and begins 1.5 to 1 second prior to movement onset [36]. In response to a warning cue, this slope is known as the contingent negative variation and will begin at the first warning cue and will decrease at a slower rate than its BP counterpart until just before the cue that initiates movement execution. Regardless of the nature of the cue, MRCPs can be generated during real or imagined movement by the person [37].

EEGs currently hold much potential for clinical and commercial applications. EEG is often recorded to diagnose conditions such as epilepsy, and are used to determine brain death in patients in a persistent vegetative state [22]. Because there is a significant amount of EEG research to help identify different types of brain activity, there is an excellent opportunity to use EEG for a variety of applications. However, for EEG to be effective, we must consider how to interpret relevant components of users' EEGs and provide an interface that results in meaningful use. These systems are known as brain-computer interfaces (BCIs) and are the key to using EEGs to their full potential.

1.3 Brain-Computer Interfaces

BCIs capture the activity in the brain (e.g., through EEG) and translate the signals into commands that can be sent into machines to carry out the desired actions [38]. BCIs provide the user with a new, non-muscular communication and control channel, a direct means of interfacing with the brain, and can used for conveying messages and commands to the external world [39]. The first BCI was proposed in 1973 by Jacques Vidal, who first explored the feasibility of a system in which "observable electrical brain signals be put to work as carriers of information in man-computer communication or for the purpose of controlling such external apparatus as prosthetic devices or spaceships" [40]. His first BCI used visual evoked responses generated from flashing lights to guide a cursor through a maze [41].

Since then, BCI technology has progressed significantly. For example, some commercial systems interpret EEG to improve meditation, with the aim to reduce stress and anxiety over long periods of time [42]. There are several varieties of systems available that will use trigger cues to interpret letters and words for communication in the otherwise mute [39]. Clinical systems are being developed that utilize neural oscillations corresponding to attention and focus to improve the symptoms of attention-deficit/hyperactivity disorder (ADHD), which shares similar behaviours with ASD [43]. These systems use neurofeedback, which display real-time feedback of the user's brain activity (either with the raw data, or through some gamified representation of the information extracted from EEG) in order to teach the users to self-regulate their brain activities [17]. It has been shown by various studies that neurofeedback can be used to help with cognitive functioning and improving behavior in people with ASD while potentially reducing dependency on medications and treatments that may pose undesirable side-effects [44]. Most research studies investigating neurofeedback tend to use smaller sample sizes (in [41] sample sizes ranged from

N=9 to N=60), and thus it is insightful to continue with more smaller studies, or less studies investigating effects across a larger population to have more justification on applying neurofeedback for ASD. Before this can occur, more studies should be conducted to be sure that such neurofeedback will work consistently across populations, as well as determine what signals can improve symptoms associated with ASD.

1.4 Brain-Computer Interfaces in Autism Spectrum Disorder

Due to the recent surge in popularity of ASD research, many BCIs are being developed to help reduce the impact of the symptoms on day-to-day functioning of the ASD population, and to supplement therapeutic interventions. Between 2008 and 2018, over 130 published works on ASD and BCI have been released on the publication database *Web of Science* (searched with the keywords "autism" and "brain-computer interfaces"). With the growing amount of research available on this topic, this section will be split into three sections: (1) Potential applications in BCI for ASD, (2) Issues related to using BCI for ASD, and (3) Popular BCI systems already being developed for ASD.

1.4.1 Potential applications in Brain-Computer Interfaces for ASD

Autism is a comorbid disorder, and as a result various other disorders are often co-diagnosed with autism. Often, commercial devices aim to assist those with ASD by addressing disorders commonly associated with ASD. While this list is nowhere near exhaustive, some common comorbidities that appear with ASD are ADHD, Epilepsy, Obsessive-Compulsive Disorder, Tourette's syndrome, and anxiety disorders. While there is no correlation between having ASD and having a comorbid disease, the symptoms that persist in comorbid disorders are similar to those in ASD and can cause significant suffering to the individual. Thus, it is beneficial to treat these disorders to improve the related symptoms of the autistic individual. There are various BCIs that address some of these comorbid conditions and can thus benefit those with ASD.

For example, BCIs systems exist to treat ADHD. Prior research has shown that children with ADHD exhibit abnormal patterns of resting theta and beta waves, which can be treated with medication or non-invasive BCIs [45]. One popular study used a non-invasive BCI to develop an attention-based game, in which the participant used their EEG signals to control an avatar via brain waves correlated with concentration [46]. It was tested on 20 children affected (but not medicated) with ADHD in 27 sessions over a five-month period. After intervention, parents reported significant improvement in their child's symptoms of ADHD, and the study reported a statistically significant improvement of children's symptoms according to the ADHD Rating Scale. Individuals with ASD and co-morbid ADHD may benefit from such a system.

BCIs can also be used to provide alternative communication channels for those with ASD. New forms of communication are important for individuals with ASD when they have communicative deficits, especially for a third of the ASD population that are categorized as non-

verbal ASD and are unable to use spoken language in a meaningful way. Some are also unable to type on keyboards due to difficulty in performing fine motor tasks. It is important to note that non-verbal autism is not a result of intellectual disability, but due to a compound of other factors [47]. Therefore, individuals with ASD may benefit from an EEG-based BCI for communication, which can manifest in various forms such as typing mechanisms, picture selection, or expressing intentions for specific actions.

1.4.2 Considerations regarding the use of BCIs for people with ASD

While a wide range of BCIs are available, there are important considerations with respect to using these systems. It is not a solution to simply take existing systems and make those with ASD use them as well, in the hopes that the expected results in other populations will be the same in those with ASD. There are special considerations that affect ASD and can affect the success of BCI systems.

The most common BCI paradigms in ASD research use ERPs, especially VEPs and P300 wave (known as the "oddball" paradigm) components. These components are implemented most often in communication-centered BCIs [39]. While BCIs based on these paradigms are beneficial for neurotypical populations who are able to take full advantage of ERPs, they may not be appropriate in a BCI developed as a communication and control tool for the ASD population. For example, BCIs using VEPs are based on counting or timing the rate of VEPs generated by flashing screens [48]. Epilepsy is a comorbid disease with ASD, and using BCIs with interfaces based on flashing lights on screens is known to be a trigger for an epileptic seizure [49]. The rate of the flashing can be reduced to minimize this risk; however the limited rate of the flashes reduced the throughput of the BCI systems. There is also evidence showing that individuals with ASD may generate unique ERPs [50]. In particular, the P300 wave components of auditory evoked potentials (AEPs), which are generated by novel auditory stimuli, are abnormal and smaller in amplitude in the group with ASD compared to the control group [51]. Therefore, using BCIs made with ERPs may not translate well over to BCIs developed for individuals with ASD because these signals are not generated the same way in individuals with ASD. If we use ERP-based BCIs on those with ASD, their intentions via their EEG may be misdetected and responded to inappropriately. In some

cases, such as VEPs, it is potentially dangerous to use these types of ERPs when developing BCIs for autistic populations.

Using some neural oscillations in BCIs are not appropriate for the ASD population, either. Several studies exist that show evidence of impaired *mu* rhythms in individuals with ASD. In the a study by Bernier et al, 14 adult participants with a condition under the ASD umbrella were asked to watch a screen that displayed people performing different gestures with their face or hands [52]. The participants were asked to observe, then imitate the gesture made while having EEG recorded. Typically, *mu* rhythms are suppressed when watching or imitating someone else perform an action. A scoring system based on the Mature Imitation Task Manual was used to assess the correctness of the gestures imitated by the participant. Compared to a neurotypical control group who also underwent the same protocol, the researchers concluded that "during the observation condition, adults with autism showed reduced *mu* wave attenuation, as compared to the typical adults" [52]. This means that the adults under the ASD group were unable to suppress *mu* rhythms the same way the control, neurotypical group could while watching the person being displayed execute the task. The researchers also identified a correlation between *mu* rhythm attenuation and how well a participant could imitate the gesture. The second study found similar results in their study, where they asked 10 high-functioning autistic participants to watch videos of a ball bouncing, their own hand moving, or another person's hand moving [28]. Similar to the results of the first study, they identified "significant *mu* suppression to self-performed hand movements but not to observed hand movements" [28]. Both of these studies suggested that people with ASD have an abnormally-functioning mirror neuron system, which inhibits their ability to observe and imitate others.

These papers concluded that the inability to elicit proper responses when the autistic individual imitates other individuals leads to deficiencies in social skills. Researchers are currently unsure of what exactly would cause this abnormal mirror neuron system.

Along with abnormal *mu* rhythms, there are a variety of studies that have looked at other abnormal functioning oscillations as well. Hashemian *et al.* [53] conducted a survey exploring different neural oscillations for diagnosing autism and severity of conditions**.** They identified studies that have found autistic abnormalities in different alpha, beta, theta, and gamma bands in the brain, particularly around the occipital and parietal lobes. Some researchers think that the abnormal MNS observed via *mu* rhythms are actually attributed to drowsiness or interfering alpha waves from some other cause [14]. However, these studies are few and far between and require more research to validate these results. Thus, these signal modalities are not recommended to be used to control BCIs. However, some of the modalities mentioned can be used in ways other than a control mechanism. By using these abnormal signals as a form of neurofeedback, people with ASD might be trained through the BCI to improve the signal's attenuation, which in turn may improve symptoms. The next section explores the most impactful BCIs in both research and commercial devices, and its feasibility in neurofeedback or as a control method.

1.4.3 Popular Brain-Computer Interfaces being developed for ASD

The efficacy of BCI-based neurofeedback was explored using 24 autistic children who were at different levels of the spectrum [54]**.** This pilot study assessed the severity of autism and problem areas identified by their family, followed by a custom neurofeedback protocol for each child in which certain frequencies were rewarded, and less desirable frequencies were inhibited. The children who completed all sessions of the experiment showed behavioural improvement, based on parent interviews and a standardized survey known as the Autism Treatment Evaluation Checklist. This improvement was independent of initial severity of symptoms and age, thus suggesting the potential in using BCIs as a supplementary therapy to improve the symptoms of ASD. It should be noted that the BCI in this case used invasive techniques to record and stimulate neurofeedback, and as a result are unlikely to be used in commercial devices.

In similar fashion, a meta-study was published examining the feasibility of neurofeedback in ASD. Holtmann et. al looked at the methodology and results of 13 impactful papers in ASD neurofeedback research [55]. The meta-study concluded that neurofeedback is not an appropriate treatment for the symptoms of ASD, because papers that reported improvement in ASD-related symptoms were only showing improvements in co-morbid conditions such as ADHD rather than improvements in ASD itself. It is valuable to see any improvement for any individual, as even small changes could positively impact the life of an autistic person. However, it was noted by Holtmann that reported improvements of symptoms tend to be based on the report of the participants' parents. This leaves the feedback open to severe biases, as parents want the best results for their children. Some parents are so desperate to helping their children that they will report superficial improvements. This is a particularly important observation in the study that was

overlooked in the conclusion. Based on the study, it is recommended that careful distinctions between improvements in comorbid conditions and ASD are identified.

Zhu et. al are developing a neurofeedback-based BCI as a form of therapy, specifically targeting mirror neuron training in people with ASD [56]. They postulate that by learning social communications in a virtual reality environment, they can improve the impaired human mirror mechanisms happening at a cortical level. Currently, they have a prototype system which incorporates action imitation and facial recognition in a virtual environment, and uses *mu* rhythms as afferent feedback on their attenuation performance [57].

Fan et. al developed a BCI that assesses the emotions of the user playing a driving simulator in a virtual reality environment [58]. During the session, the user's EEG was recorded and classified based on feelings of frustration, engagement, boredom, difficulty, and enjoyment. While this study had an overarching goal of using the environment for autism intervention, it focused on adapting the system to the user for optimal performance. This is a reversed approach from the other studies discussed, as the goal of the BCIs mentioned in other studies aimed to teach the user to adapt to the system instead. With this approach, the researchers believed that this would create a more enriching environment to teach specialized skills (i.e., driving) to people with ASD. More research is needed comparing this approach to standard methods in order to evaluate if it improves performance success with BCIs, compared to the traditional approach.

Some BCIs have broken past the barriers of research and are now being developed as commercial devices. For example, Muse is a BCI developed by the company Interaxon that uses EEG collected on the forehead to give feedback on meditation performance. Dreem is another company that has developed a commercial BCI product to measure quality of sleep.

While commercial BCIs have existed for some time, only recently have there been BCIs developed targeting at ASD populations. Prior research is now able to show that there may be a benefit in having BCIs made for people with ASD [7]. However, traditional paradigms used for neurotypical populations may not suffice both in terms of what brain signal modalities are used, and how the interface is perceived by the target population.

1.5 Movement Related Cortical Potentials and Hebbian Plasticity

In order to properly explore the mirror-neuron hypothesis for ASD, all brain signals elicited in the motor cortex need to be explored in order to identify what functions are impaired, rather than just focusing on *mu* rhythms (as is done in research). MRCPs are of particular interest because they are elicited at the same location of the scalp as *mu* rhythms and are also related to the intention of movement. Unlike *mu* rhythms, they can be detected prior to movement and give insight about the cortical processes preparing for the movement. As a result, the user's intention to move can be decoded in real-time and provide near-instant feedback [59]. The user's MRCP is elicited during both overt and covert movement intentions. This is valuable for real-time control and can be applied to a variety of situations such as self-controlled neuroprosthetics, self-paced rehabilitation, and communication. Therefore, MRCPs should be explored as they may provide more insight on the mechanisms of their mirror neuron system. This is the focus of this research, and to the author's knowledge, the first time this EEG signal has been explored in ASD research.

There are several ways to detect MRCPs in a user's EEG. Currently, the best approach uses locality preserved projections (LPPs) to extract feature components in the EEG. The resulting features are a low-dimensional representation of the original EEG signal and are used to train a machine learning algorithm that is designed to detect whether an MRCP event is occurring or not. While other methods exist to extract features to represent an EEG event such as PCA, LPP is able to preserve the local structure (distances of neighboring samples) in the high-dimensional data after dimensional reduction. In comparison, other methods such as PCA usually change the local structure of the original high-dimensional data after dimensional reduction. If the data lost contributed to the discrimination between different classes, then the resulting classifier is less effective.

The use of MRCP systems have already been demonstrated successfully in the use of neurotherapy, particularly for improving motor functioning. In Ru et al, a BCI was implemented that used the intention of movement to trigger the functional electrical stimulation of the foot in an effort to help stroke patients recover voluntary control of their foot [60]. While autistic populations typically have voluntary motor control and thus do not require restoring the activation of their muscles, the cognitive mechanisms improved by MRCP neurofeedback could benefit those with ASD by strengthening the connections within the neurons in the sensorimotor cortex.

Research in MRCP is important because MRCP is one of the few signals that can be detected prior to an intentional action performed by the user. Because it can be used to predict when a user will move, it can provide real-time feedback to the user quickly enough to achieve Hebbian learning. Hebbian learning is a theory in which repeated simultaneous activation of cells strengthens the synaptic connections between them [61]. As a result, mechanisms such as muscle control that has been lost can be regained by triggering neurofeedback, such that information sent to the brain by muscle and sensory nerves are strengthened by the intention of that movement. Neurofeedback aims to close the loop of cause-and-effect by using the intentions from the user to rebuild the synapses that may have been severed through some condition or illness.

Hebbian plasticity is considered an important contribution to how mirror neurons are developed. It is believed that the activation of mirror neurons will coincide with the sensory feedback (audio, visual, and touch) from the action taken. When the individual watches someone else perform an action, the same neurons that would be activated as if the self were performing the action are activated [62]. As a result, the mirror neuron system is a result of Hebbian learning due to the plasticity of the brain. It is hypothesized that Hebbian plasticity from the mirror neuron system helps predict what an individual is feeling or will do next, based on the perceiver's own

system [27]. In order to achieve Hebbian plasticity with BCIs, neurofeedback has to occur within 200 milliseconds after the action has occurred [63]. If we can use neurofeedback to improve these systems, they can help improve the deficits experienced by those with ASD. However, *mu* rhythms (which represent the activation of the mirror neuron system) cannot be used by BCIs to achieve Hebbian learning because they are not easily identified in EEG until several seconds after the action is imagined or initiated by the user. Since MRCPs can be detected prior to the movement, neurofeedback can be provided to the user within the window required for Hebbian learning. Thus, it is of significant value to analyse how MRCPs are elicited between neurotypical and autistic populations in order to find successful neurofeedback mechanisms that can trigger Hebbian learning that can be used to improve the symptoms or cognitive functioning of these individuals.

The MNS is shown to have abnormal activation in individuals with Autism. If we can use neurofeedback to improve the activation of the MNS then we can potentially improve the deficits in ASD. However, neurofeedback with *mu* rhythms is currently not possible due to the delay in its detection, which is outside of the window needed to achieve Hebbian plasticity to strengthen and rebuild severed connections between neurons. MRCPs do not have this delay and thus may be a better alternative for neurofeedback to improve the symptoms experienced by those with ASD. Prolonged MRCP neurofeedback can strengthen the synapses in the motor cortex and recruit more neurons for motor-based actions [35]. The *mu* rhythms in MNS activation is related to the motors systems also activated in MRCP, so MRCP-based neurofeedback may also improve MNS activation itself. However, it remains that the differences in MRCPs are examined between neurotypical adults and those with ASD in order to better understand how the morphology of MRCP may differ between these groups. If we can demonstrate success with MRCP detection then

it opens the possibility of designing a neurofeedback system could be designed as an alternative form of neurotherapy.

1.6 Objectives of thesis research

From the literature review, there appear to be several gaps around the use of *mu* rhythms to describe the MNS hypothesis in the ASD population. There are other representations of similar motor systems activated with mu rhythms that have not been explored. To the knowledge of the author, MRCPs have never been studied and compared between ASD and neurotypical populations. Furthermore, the effect that different interface cues may have on MRCPs in the ASD population given their hypersensitivity to stimuli is largely unexplored. Differences between signal elicitation as well as perceived interactions with these cues need to be compared. Therefore, it is worthwhile to explore if there is a difference in MRCP elicitation in ASD populations, and if so, how that may change the way we perceive this *mu* rhythm-MNS hypothesis.

The potential for BCIs to help ASD populations as a new form of communication, control, and neurotherapy has been demonstrated through previous work. However, several questions still remain regarding how to interface with the brainwaves of people with ASD and how their brain signals could impact BCI design.

The overall goal of the research presented in this thesis is to gain an understanding of how individuals with ASD respond to different prompting modalities compared neurotypical controls. The research questions that guided this thesis are:

1. What is the quantitative EEG response of people with ASD to auditory, haptic, and visual BCI sensory modalities?
2. How do people with ASD subjectively perceive their interaction with auditory, haptic, and visual sensory stimulation?

3. How do movement-related cortical potentials compare between people with ASD and neurotypical controls?

An experiment was conducted to answer these questions; the details of this experiment are outlined in the Methodology in section 2. Then, the results are presented in section 3, which compare MRCP features between the ASD and neurotypical groups. Section 4 discusses why MRCP features may be reduced in the ASD population, and how these are interpreted with respect to the qualitative survey data collected. Section 5 reflects on three concerns identified in this research. Finally, the concluding remarks and recommendations are highlighted in section 6. This thesis encapsulates the findings from the outlined experiment.

2. Methodology

A mixed-methods approach was taken by gathering both qualitative and quantitative data to provide a holistic view of the BCI system. The purpose of the data collection and analysis is to gain insights regarding as to how MRCPs may differ between ASD and neurotypical populations as well as whether there are individual differences between participants with ASD.

2.1 Participant Recruitment

10 ASD participants with moderate to high-functioning conditions were recruited from private support groups and within the Autism Society of Ontario. 10 neurotypical participants were also recruited as neurotypical controls (age and sex-matched to the best of the author's abilities) from the University of Waterloo. Both groups had to follow separate inclusion and exclusion criteria in order to participate. Both groups had inclusion and exclusion criteria, which is described in TABLE 1.

TABLE 1 Inclusion and exclusion criteria for study participants.

	Inclusion criteria	**Exclusion criteria**
Neurotypical group	• 18-35 years of age • Fluent in the English language • Competent to consent	• Satisfies any of the exclusion criteria in the ASD group • Have any of the following conditions: 1. Autism Spectrum Disorder (ASD) 2. Asperger's Syndrome 3. Down's Syndrome 4. A pervasive developmental disorder not otherwise specified (PDD-NOS) 5. Epilepsy or a history of seizures
ASD group	• Satisfies inclusion criteria of neurotypical group • Have a diagnosis of ASD (HF/MF-ASD) via a formal diagnostic report from a physician or clinical psychologist • Are competent to consent based on the subjects' ability to provide a spontaneous narrative description of the key elements of the study	• Have a motor-related illness or disease that inhibits voluntary limb control • Any known neurological disorders and any known allergies to the ingredients in the conductive gel (including: aqua, carbomer, hydroxyethilcellulose, potassium chloride, sodium hydroxide, propylene glycol, methychloroisothiazolinone, and methylisothiazolinone). • Any vibration or musculoskeletal disorders affecting the hand (such as carpal tunnel syndrome, hand-arm vibration syndrome, or De Quarvain's). • Has had previous nerve damage to upper extremities • Has arthritis, obesity, diabetes, tendinitis, thyroid disease, or kidney function disorders • Is pregnant • Currently undergoing menopause

2.2 Ethics Clearance for Protocol

The study received approval by the Office of Research Ethics at the University of Waterloo (ID#: 22233), which includes the use of all apparatuses outlined in section 2.3 below.

2.3 Apparatus

Participants' signals were collected with commercially available devices (listed below), with the exception of a haptic wristband, which applies vibrotactile stimulation using a linear resonant actuator (10mm, C10-100, Precision Microdrives Ltd.) controlled by a computer soundcard (Sound BlasterX G1). The haptic wristband was approved for use by the Safety Office at the University of Waterloo and was seemed safe for use in the study.

The devices used for biosignal acquisition were three g.USBamp bioamplifiers, and three interfaces for the electrodes (g.GAMMAbox) that connects the active EEG electrodes on the EEG cap to the bioamplifiers, which are then connected to a desktop via USB cable for signal processing and data analysis. The interfaces and data acquisition software were built in C++, and MATLAB and Minitab 18 were used for the data analysis.

2.4 Experimental Protocol

The experiment was partially-balanced and pseudo-random to the participants. Each participant was assigned to one of six subgroups that determined the order of interfaces the participant interacts with. The structure of experiment sessions for these subgroups were identical, other than the order of cue types being presented. In the experiment, the participant was asked to sit in a chair and perform either dorsiflexion or imagined dorsiflexion (with intention of movement but without physical movement) of their dominant foot, timed to different types of cues. Then, the participant was asked to report their experiences on a survey (see FIGURE 9 in the Appendix) that captured the subjective perception of a brain-computer interface. After all the interface cues were interacted with, the participant was asked to rank their preference of interface for real movement, and then again for the imagined movement.

Before the data recording, surface EEG electrodes were attached to the participant's scalp, and EMG electrodes were placed over the mid-section of the Tibialis Anterior muscle of their dominant leg. Once the electrodes were prepared and adhered to the skin of the participant, they were asked to interact with three different interfaces, in which different modalities of cue were presented:

1. Auditory: A voice counted down each second ("three, two, one, go"), followed by a "Go." At the "go" cue the participant performed the task.
2. Visual: A red square box appeared and disappeared four times. The box flashed first at the edge of the cross, and discreetly appeared closer to the center of the cross with each flash. When the square appeared at the center it turned green, at which point the participant performed the task.

3. Haptic: There was a wristband that vibrated on the participant's wrist. At each second leading up to the "go" cue, the band vibrated in a short burst. This happened three times. At the fourth vibration (the "go" cue) the vibration was more prominent and lasted longer, during which the participant performed the task.

The design of each interface is illustrated in FIGURE 2. The participant interacted with each interface twice, performing real dorsiflexion movement first and then imagined dorsiflexion movement. The interface modalities were presented to the user in a pseudorandom order. While they are not necessarily representative of stimuli experienced in daily life, they are sufficient to measure EEG responses and compare reliably between the cues.

For each BCI, the participants were asked to wait for a cross to appear on the television screen in front of them. The cross indicated the beginning of the trial. The participant was asked to avoid performing any sudden jerking movements during this period in order to prevent strong motion artifacts in the EEG recording. For the first half of the experiment, the participant performed dorsiflexion of their dominant foot as the task. In the second half of the experiment, the participant was asked to imagine performing the same dorsiflexion task rather than physically performing it.

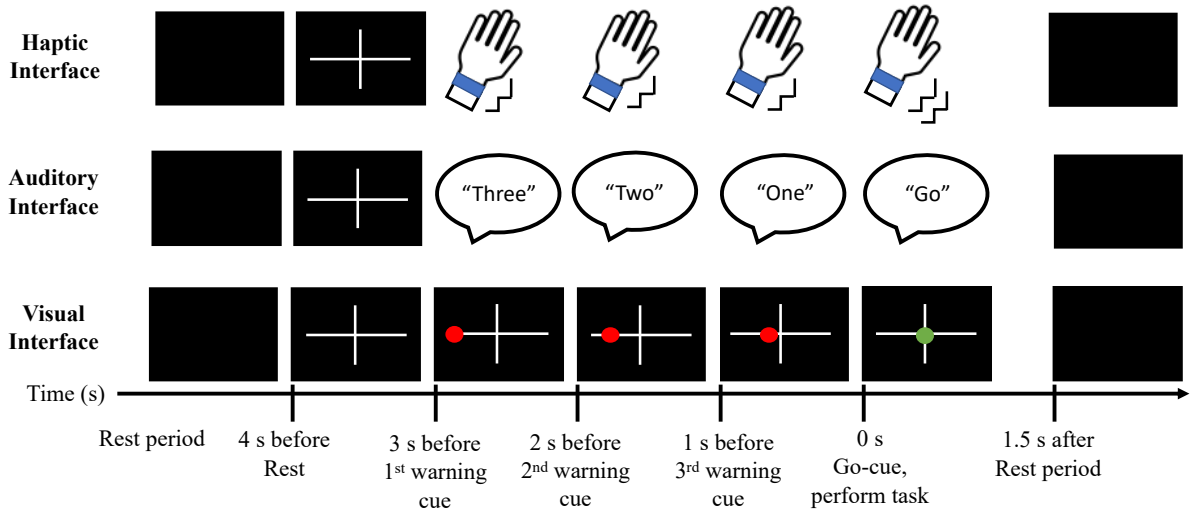


FIGURE 2 A side-by-side comparison of the three interfaces used in the experiment.

For each of the interfaces, the participant performed the same task 20 times in a row. Each task took about six seconds to complete; as such each run lasted about 90 seconds. Each session had a total of six partially-balanced pseudorandom runs, which will have one of six orders based on the order group the participant is assigned to (see TABLE 2).

TABLE 2 The order of interfaces presented for each group. Each participant was randomly assigned to one of the order groups.

Order Group	First real movement interface	Second real movement interface	Third real movement interface	First imagined movement interface	Second imagined movement interface	Third imagined movement interface
1	Auditory	Visual	Haptic	Haptic	Auditory	Visual
2	Visual	Auditory	Haptic	Haptic	Visual	Auditory
3	Haptic	Auditory	Visual	Auditory	Visual	Haptic
4	Haptic	Visual	Auditory	Visual	Auditory	Haptic
5	Visual	Haptic	Auditory	Auditory	Haptic	Visual
6	Auditory	Haptic	Visual	Visual	Haptic	Auditory

Each row is the order of conditions the participant performed the task in. After each run (which has 20 trials of the task in each), the participant was given a brief two-minute break, during which they were asked to fill out the questionnaire. A sample of the survey can be found in FIGURE 9 in the Appendix. Every three runs, the participant had a longer break of about five minutes, between the "real movement" task and the "imaginary movement" task. During this break, we asked the participant to rank, in descending order, their most-to-least preferred interface to work with. The participant has a total of six conditions they have performed the task in. The entire session lasted between 1-2 hours, including the preparation and removal of the electrodes. After the session, each participant had a set of qualitative data (as questionnaires) as well as the quantitative EEG data that was recorded from the session.

2.5 Data Analysis

2.5.1 Data Preprocessing

Prior to data analysis, the EEG signals were filtered to remove unwanted noise from the EEG signals. To extract MRCP, a 4th-order Butterworth filter between 0.05 Hz and 3 Hz was applied to the data, followed by a large Laplacian spatial filter was used centered at Cz (the electrode site in which MRCP is most pronounced with dorsiflexion). Cz is located in the center of FIGURE 1. These techniques were selected based on its success in other research [59][64]. It is known that the initial negative deflection of the MRCP begins at the first cue, which occurred three seconds prior to movement onset in the current experimental protocol. The MRCP would rebound after movement onset until approximately 1.5 seconds after movement onset. Thus, epochs for each trial were retrieved from 4s before movement onset (when the user reacts to the 'go' cue) to 2 seconds after. Movement onset was detected using the Teaker-Kaiser Energy Operator to condition the EMG channel. Feature extraction was performed on the preprocessed epochs, followed by a statistical analysis on these features described in Section 2.5.2. FIGURE 3 depicts what the data looks like after these filters are applied and the data is organized into epochs.

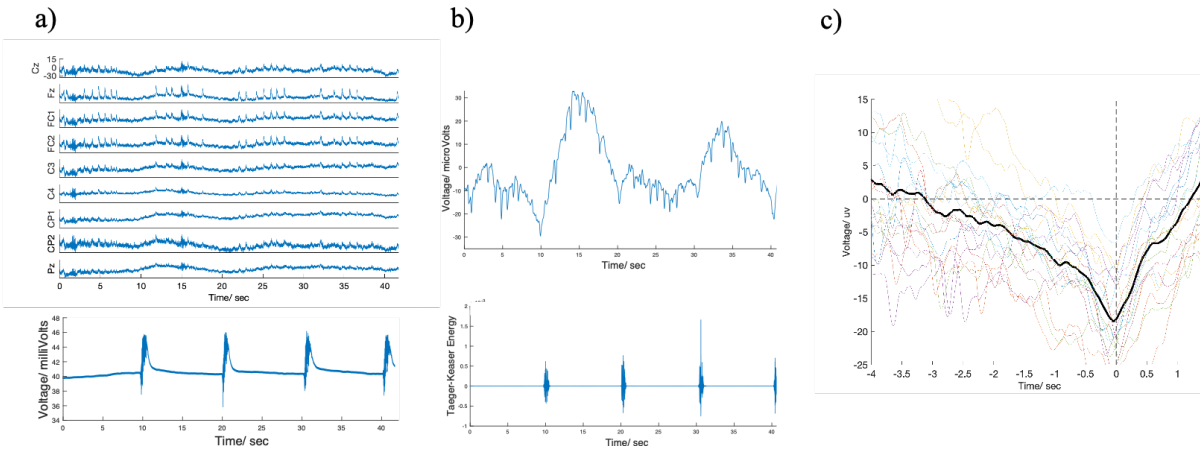


FIGURE 3 Different stages of preprocessing the EEG data: a) The EEG data and EMG data is retrieved and filtered with a 4th order Butterworth filter. The EEG data around Cz is pictured in the top channel, and the EMG channel is at the bottom. b) A large Laplacian spatial filter is applied about Cz. Epochs are aligned using movement onset in the EMG, indicated here as peaks in the conditioned EMG channel. c) EEG epochs are averaged across trials and is used for feature extraction.

2.5.2 Feature Extraction

The feature set is described by Farina et al and consists of four components [65]. The first component calculated is the peak amplitude of negativity (PA), which is the point of largest negative magnitude between 0.5 seconds before to 0.5 seconds after the 'go' cue is presented. Typically, there is a variable delay among participants between the moment of the appearance of the 'go' cue and the moment of movement onset. Because participants will react at different times with respect to this cue, we calculated all other features from the moment of this peak. The second component is called the first negative slope (NS1) and describes the slope of the EEG data between the first cue and 1.5 seconds before PA. The third component, known as the second negative slope (NS2), is the slope between 1.5 seconds prior and up to the moment of movement onset by the user. The fourth component is known as the rebound rate (RR) and is the positive slope of the EEG recorded between movement onset and 1.5 seconds after movement onset. FIGURE 4 depicts how these MRCP features are represented in the data. These features are used to compare the quantitative trends in the data between different interfaces and groups.

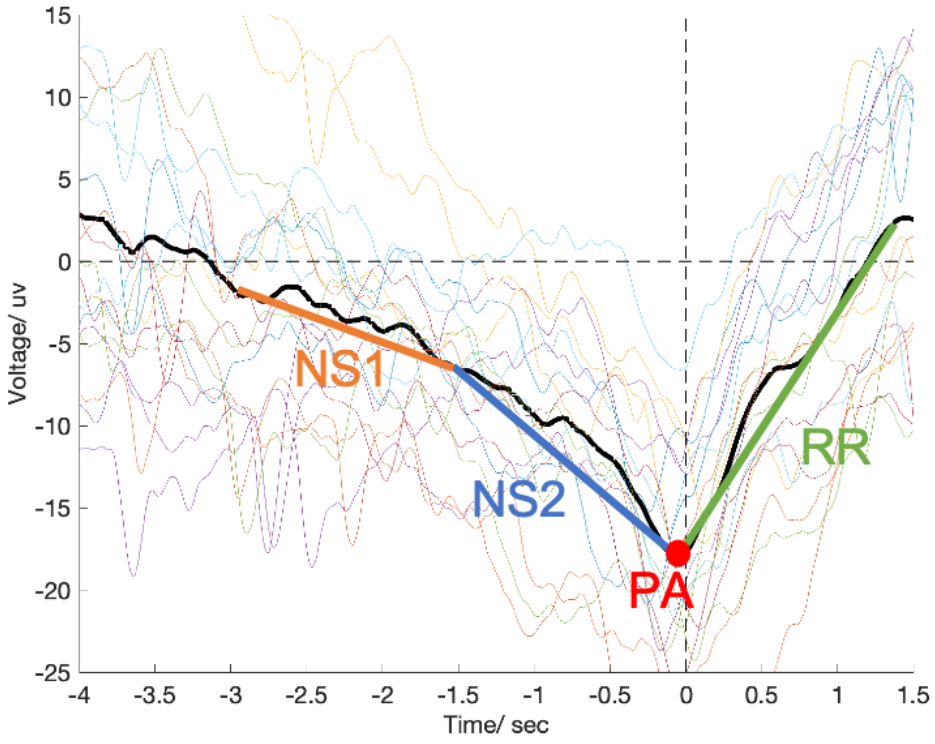


FIGURE 4 The features that represent the average MRCP events from a neurotypical participant. Time 0 is the moment of movement onset as detected in EMG. NS1, NS2, PA, and RR represent the four features of MRCP as described by Farina et al [65]. It should be noted that the time of peak amplitude (PA) is not exactly at 0 due to differences in reaction time between individuals. This is very common and does not affect detection or timing in MRCP-based BCIs.

Each participant performed 20 trials of each task for each condition (i.e., Real movement + Auditory, Real movement + Haptic, Real movement + Visual, Imagined movement + Auditory, Imagined movement + Haptic, and Imagined movement + Visual). For each condition, the average MRCP event across all 20 trials were calculated, and then the NS1, NS2, PA, and RR features were calculated from the average signal. The ensemble average of EEG signals has been accepted as a common practice in ERP analysis because of the varying and poor signal-to-noise ratio (SNR) in the EEG data – while the signal that is desired for analysis is always present in the event (in our case, as indicated by a cue or EMG movement onset) the background noise is uncorrelated with signal and thus can be averaged out to identify the consistent MRCP signal in each epoch. Thus, ensemble averaging is used to improve the SNR and facilitating subsequent feature extraction. These features will be used to inform our statistical model that will identify any statistically significant changes in MRCP between conditions.

A second feature set is extracted and used for MRCP detection. A variety of methods have been proposed and developed to predict if movement intention is occurring in a user. Some methods that have been explored use matched filters [66], common spatial filters [67], and locality sensitive discriminant analyses, but are not widely recognized in MRCP research [68]. In current models used for MRCP detection, the features that are used for MRCP event detection in this study are components extracted with locality preserved projections (LPP). These components are then used to train a machine learning model that will learn to determine if MRCP is occurring in a set of EEG data or not.

2.5.3 Statistical analysis

It is common in BCI research to use the analysis of variance (ANOVA) statistical test to identify statistically significant differences between sampled means of different conditions or environmental effects on EEG signals [5][6]. In EEG studies, this process consists of taking the average of individual trials across all experimental conditions, and then conducting the ANOVA test to determine if a controlled condition or variable can cause a change in the EEG signals, and whether the resulting differences are statistically significant. There are three conditions that must be satisfied in order to have a reliable ANOVA test: (1) all conditions contain independent samples, (2) the response variables (NS1, NS2, PA, RR) are gaussian-distributed, and (3) the variance of the dependent variables are the same. Researchers have already proven empirically that EEG data rarely satisfies these assumptions, making it unlikely that it is an appropriate analysis method [4].

Furthermore, Vossen et al argues that ANOVA is an inappropriate statistical model for ERP analysis due to the loss of within-subject variance between different trials, and the requirement of having a sufficient number of artifact-free trials for analysis [69]. Instead, Vossen et al recommend using a mixed regression approach to ERP-based studies. They were also able to show that ANOVA and mixed regression approaches yield similar results, with the key differences lying in the robustness of the model. With mixed regression, all trials can be used instead of an ensembled average of the ERP data, meaning that less trials have to be rejected and can provide more insights to within-subject variations over time.

A linear mixed model (LMM) is a type of mixed regression approach and shares some important similarities with ANOVA in that both methods attempt to fit a linear relationship between factors. However, LMMs make distinctions between fixed and random effects between conditions in the data. Due to the high variability of ERPs within subjects, this is considered a

random factor. Because ANOVA tests do not allow random factors, there is strong motivation to use LMMs instead. Several studies have used LMMs in their studies [70], [71].

To determine if there is a statistically significant change in MRCP between neurotypical and autistic populations, a linear mixed-effect model was produced in which the fixed factors were the type of interface (auditory, visual, and haptic), the type of task executed (imagined or real), and the group of interest (neurotypical vs ASD group). The subject is incorporated into the model as a random correlated effect, which is nested within the factor of group of interest (neurotypical vs ASD group). The response variables are the MRCP features NS1, NS2, PA, and RR.

With this model, a Type 3 test of Fixed Effects was conducted, which tests the significance of fixed effects present in a dataset. If a fixed effect has statistical significance, it means that the conditions can predictably affect some selected response variable. The Type 3 test of Fixed Effects is conducted to determine the significance for each factor, as well as potential two-way effects between ASD and interface cues. This test is conducted by constructing a type L matrix for each effect, and then calculating the obtained F score for each effect. The F score determines how likely the factor being tested has caused a change in the response variable. Each F score is compared to a threshold F value that, if surpassed, indicates that there is a significant difference observed (and that the observed difference is not due to a sampling error). Most statistical tests on MRCP data use a = 0.05 (analogous to P-value), so that is maintained in the Type 3 test for consistency [72]. The LMM and Type 3 test of Fixed Effects is conducted using the Minitab 18 software.

2.6 Qualitative Survey Data

Each participant was asked to complete a set of qualitative data using questionnaires. To standardize part of the qualitative assessment, we have asked each participant to rank their preference of the interface type from most-preferred to least-preferred. We use this to compare the preference ranking to their strongest-performing interface with the EEG data, as well as comparing their rankings with how they immediately reported their feelings after interacting with a particular interface. The questionnaire can be found in FIGURE 9 of the Appendix, and the justification for each question are as follows:

The first question on the survey is used to compare the usability of interfaces between participants. The average of these Likert scales will be used to compare against what interface was ranked as the highest and lowest for each user, as well as provide insight to the perception of real and imagined interfaces.

In the second question of the survey, we leave a dialogue box open for text. While methods exist to perform a standardized analysis for similar open-ended questions, writing in the box is optional and thus not all of the participants responded. As a result, there is an incomplete set of data for an already small sample size. As this was an exploratory part of the study, the benefits of such standardized techniques will not provide enough insight to conduct. A descriptive analysis of these responses provide context to the quantitative data, which informs the understanding of the results. A human factors approach was taken by identifying recurring themes in their responses and comparing any indicated struggles or ease-of-use against the quantitative data to see if they align. Particularly of interest to this research is if any reported sensitivities to particular interfaces affect how participants respond to the first and last question of the questionnaire.

The last question is used to determine the feasibility of the interface being evaluated. The previous questions do not explicitly determine whether the participant would use this in a real-world situation, thus this last question must be asked to determine if such an interface would actually be adopted in a more casual setting (as BCIs are designed to operate in). The binary responses are converted into a usability rate, and then the Adjusted-Wald bionomial confidence interval is used to extract confidence intervals to predict the potential usability. The Adjusted-Wald confidence interval is used to its appropriateness for small sample sizes [73].

3. Results

3.1 Participants

The EEG data of ten neurotypical participants were recruited so as to age and sex-match to the ASD participants as closely as possible. All participants were recruited within one hundred kilometres of the research lab in Waterloo, Ontario. TABLE 3 reports the demographics of the participants recruited.

TABLE 3 Participant demographics.

Group	Mean Reported Age (Standard Deviation)	Number of men	Number of women
ASD	25.0 (6.5)	5	5
Neurotypical	27.5 (6.7)	5	5

A set of EEG data and survey responses were recorded for each interface and movement execution and imagery for every participant. An example of the quantitative data from a neurotypical participant's EEG is in TABLE 4. As the interface cue types were presented in a balanced, random order to the participants, TABLE 4 does not reflect the order that the participant completed each run. The interface cue type was not included in these descriptive statistics because they were not found to have statistically significant differences on their EEG values (see TABLE 6).

TABLE 4 An example set of data collected for one participant from the neurotypical group.

Type of Movement	Interface Cue Type	NS1 (μV/s)	NS2 (μV/s)	PA (μV)	RR (μV/s)
Real	Haptic	-13.689	-12.4655	-19.4868	15.9445
Real	Visual	-9.3711	-10.6046	-15.9635	14.6782
Real	Auditory	-10.9719	-12.4589	-18.0024	15.5910
Imaginary	Haptic	-2.8565	-4.6599	-7.9625	6.9437
Imaginary	Visual	-6.2371	-5.2812	-8.7225	6.4788
Imaginary	Auditory	-6.0281	-3.5665	-7.5247	5.9898

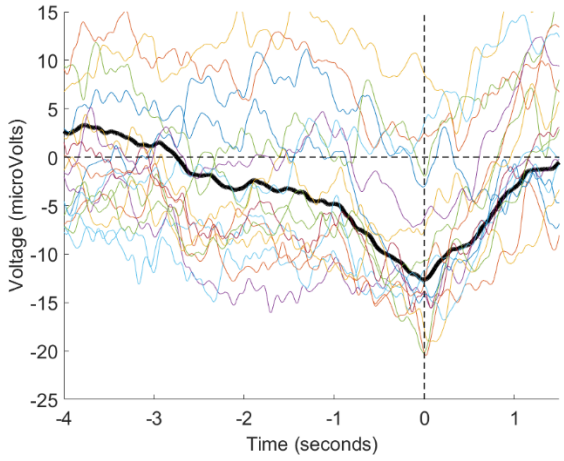
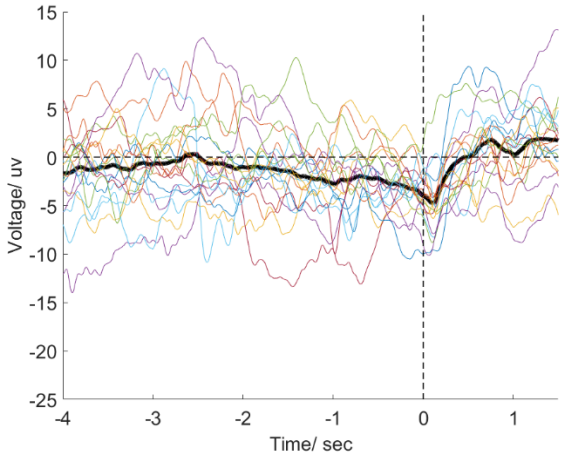
The responses from the surveys can be found in section 3.3.2, and their reported preference rankings can be found in section 3.3.1.

3.1.1 Case study comparing participants

A small case study is presented to illustrate the differences observed in the EEG data between ASD and neurotypical participants, which are shown in TABLE 5. Both participants are a typical representation of their groups. For example, all of the neurotypical participant's features are within 3 μV of the mean real-movement MRCP features in FIGURE 6 (less than 1 standard deviation from the mean features as indicated by the error bars), and all of the features from the typical ASD participant are within 1 standard deviation of the mean of the ASD features in FIGURE 7.

The features shown were calculated during real movement execution and with an auditory interface. The real movement BCI was chosen to better illustrate the observations in the EEG data, and the auditory interface was arbitrarily chosen since there are no statistical differences between interfaces (see TABLE 6).

TABLE 5 The EEG epochs and features calculated from the average (demonstrated in the graph as the black signal) for a representative ASD and neurotypical participant.

Representative naïve neurotypical participant	**Representative naïve ASD participant**
	

Features:			
NS1 (μV/s)	-10.7357	NS1 (μV/s)	-1.9713
NS2 (μV/s)	-6.0791	NS2 (μV/s)	-4.2650
PA (μV)	-12.5947	PA (μV)	-4.7455
RR (μV/s)	7.9762	RR (μV/s)	4.2836

There are three observations that can be made from TABLE 5:

1. The ASD participant has less inter-trial variation in their EEG features than the neurotypical control. The neurotypical participant has high inter-trial variability but elicits more pronounced features.
2. The peak amplitude of negativity (PA) is much larger in the neurotypical participant than the ASD participant.
3. In the ASD participant, the potential after movement execution is higher than the baseline potential prior to the MRCP.

The first and second observations are consistent in most participants. The third observation can be found amongst most participants in the ASD group, but is not consistent in for all participants.

3.1.2 Unrepresentative subject – AS07

The data of one subject from the ASD group was rejected from the statistical analysis. The subject is very high-functioning. The MRCP features of this subject are very prominent and have low variance. The MRCP features for this subject are significantly different from the rest of the ASD group. Across all interfaces, the MRCP features of AS07 are significantly different than the features calculated for the rest of the group. To confirm this, four t-tests were conducted (one for each feature) to see if the MRCP features in AS07 are significantly different from the rest of the ASD group. A t-test validated these differences with a significance of $p < 0.0001$ for all of the features. While this participant elicits a very desirable MRCP, it is unrepresentative of the neurotypical or ASD groups. As a result, this subject's data was removed from the statistical analyses in section 3.2.1.

Since this data is uncorrupted and still useful for other analyses, it is still included in the descriptive statistics in sections 3.1.3 and 3.1.4 as well as the qualitative analysis presented in section 3.3. FIGURE 5 illustrates this subject's data. Compared to the case study presented in section 3.1.1, it is evident that subject's data is very different. It should be noted that this subject was also naïve to BCI, and thus did not have any training prior to improve MRCP elicitation.

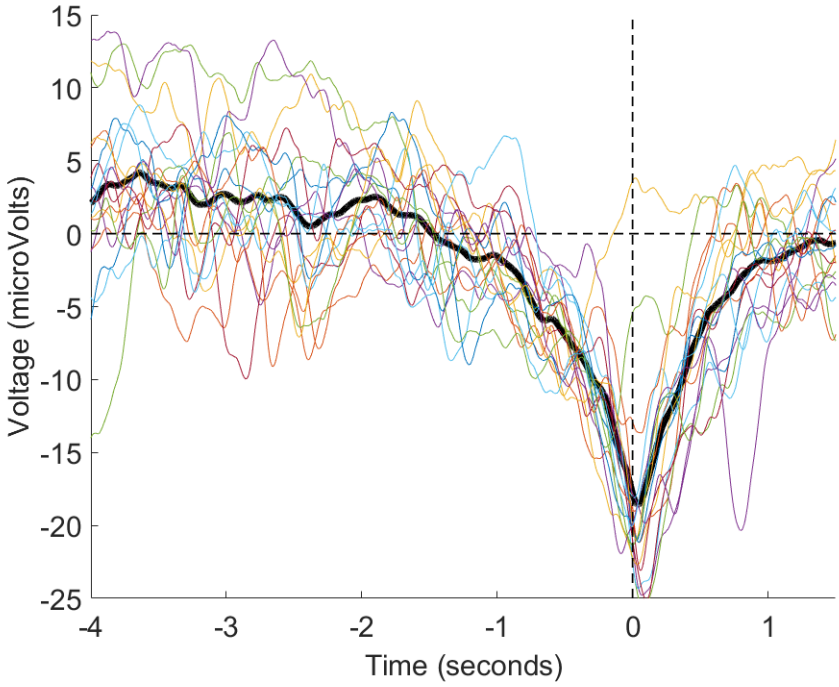


FIGURE 5 An example of one of the runs of the rejected subject. This particular visualization is from the subject's real movement execution with an auditory interface.

3.1.3 Neurotypical group

A total of fifteen neurotypical subjects were recruited for the study. Five of them were removed from the EEG analysis due to an abundance of noise and movement artifacts in their data, or not being close enough to the age and sex of the ASD participants to match to. Two neurotypical subjects had their real-movement with haptic interface run removed due to executing dorsiflexion at incorrect times in the EMG data collected. This resulted in the analysis of the data from all ten neurotypical participants, but two conditions from the real movement with haptic interface condition were removed.

While the rejected runs from two neurotypical participants still have valuable qualitative data, it is not considered when compared to the ASD group's survey data to maintain consistency in the comparison. FIGURE 6 displays the mean and standard deviation of the MRCP features collected from the neurotypical group for real and imagined movements. The mean values for NS1, NS2, PA, and RR were calculated across all of the interfaces. Note that all features in the imagined movement MRCP are smaller in value compared to their real movement counterpart.

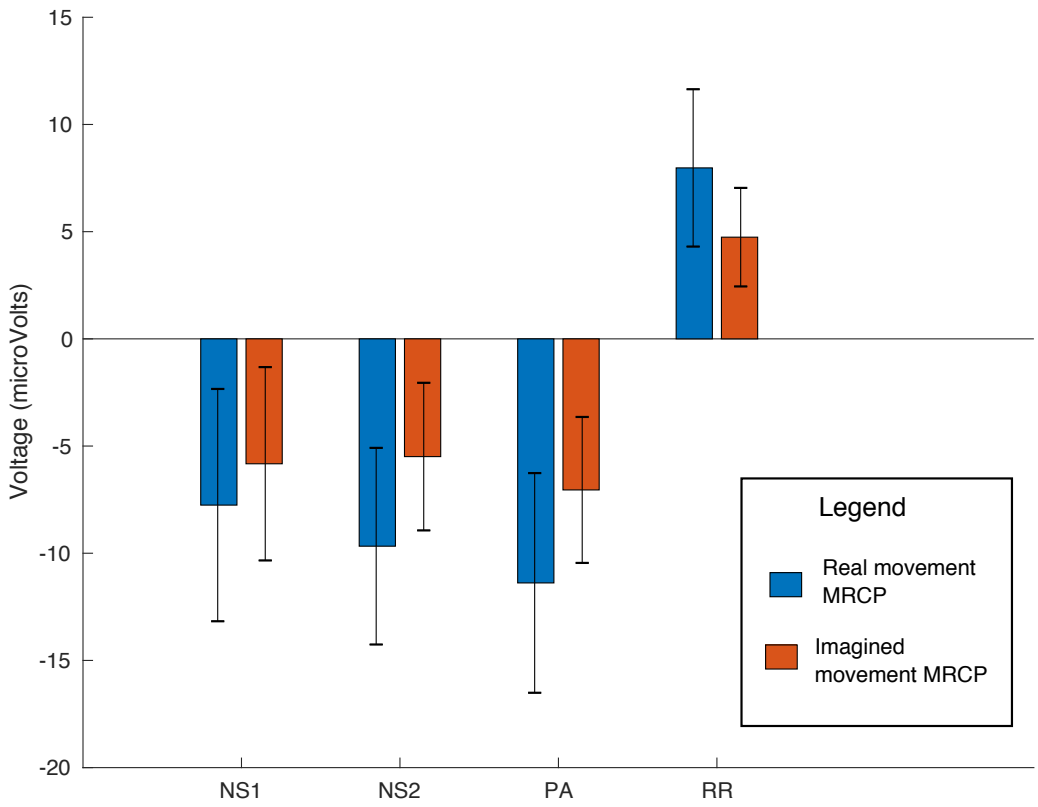


FIGURE 6 The mean values across the four MRCP features computed for real and imagined movement MRCP in the neurotypical group. The error bars indicate the standard deviation for each feature. Note that for features NS1, NS2, and RR the voltage is measured over one second.

Of the same ten participants used for quantitative analysis, six of them responded to all parts of the qualitative survey. The other four did not report their preference ranking, and thus are not included in qualitative analyses using the preference rankings in TABLE 9.

3.1.4 ASD group

All ten sets of data collected in the ASD group are used in the quantitative and qualitative analyses. In the qualitative data set, three of the ten participants did not report their rankings of preference of cue type. As discussed in section 3.1.3, those who did not report preference rankings were excluded from the analyses that use preference rankings in TABLE 9.

FIGURE 7 shows the mean features across all interfaces, separated by movement execution type. The large standard deviation represented by the error bars show that there is a lot of variance during real movement execution. While the imagined movement features are less variable, the mean values are closer to 0 μV.

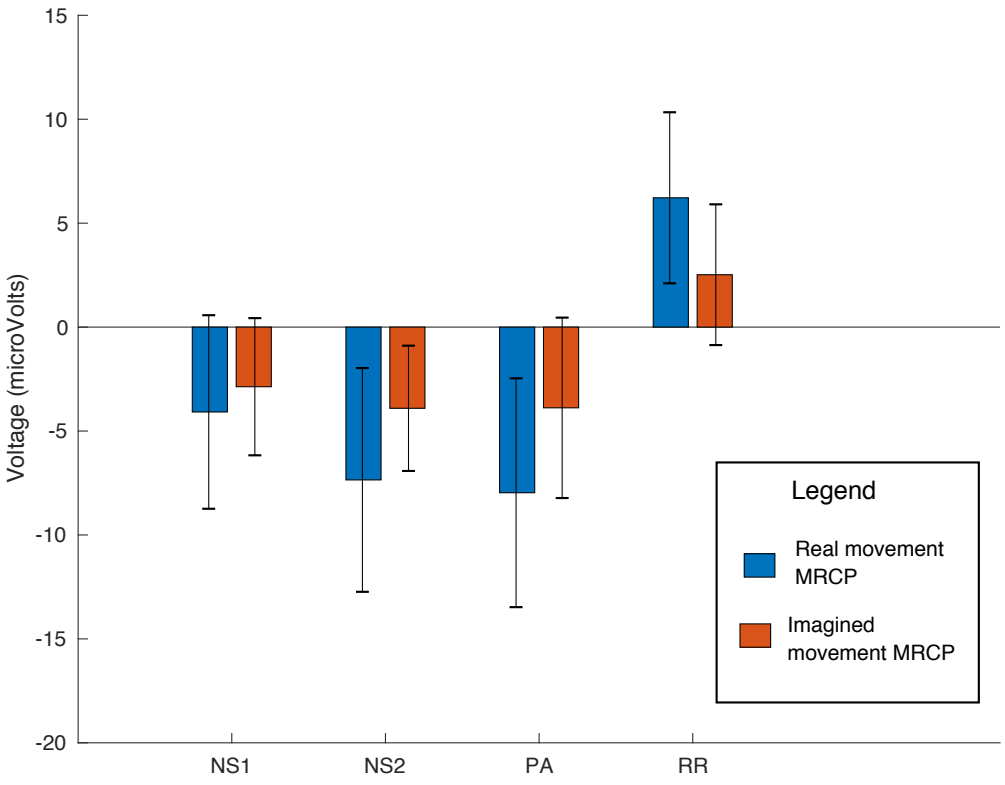


FIGURE 7 The mean values across the four MRCP features computed for real and imagined movement MRCP in the ASD group. The error bars indicate the standard deviation for each feature. Note that for features NS1, NS2, and RR the voltage is measured over one second.

3.2 Quantitative Analysis

3.2.1 Comparison of MRCP Features

To compare the MRCP features between the neurotypical and ASD group, the mean feature values for both groups are placed side-by-side in FIGURE 8.

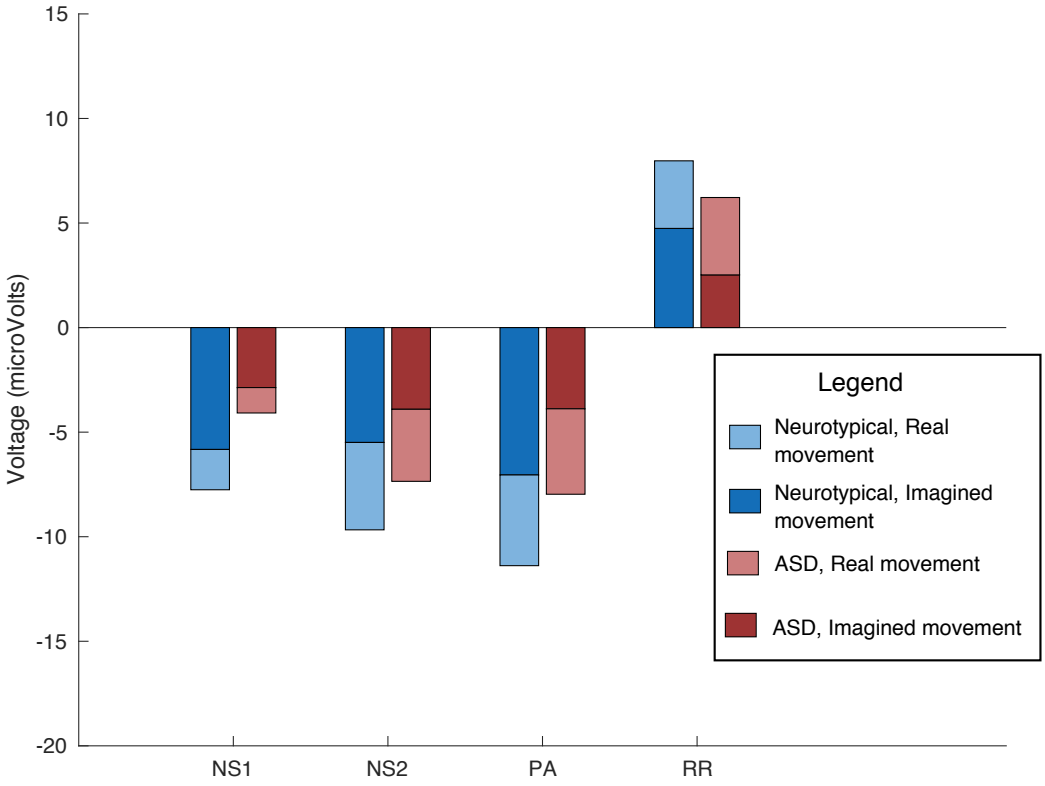


FIGURE 8 Mean values of MRCP features between the neurotypical and ASD groups. Note that for features NS1, NS2, and RR the voltage is measured over one second.

To measure the statistical strength between these differences, a Type 3 Test of Fixed Effects was conducted according to the methodology described in Section 2.5.3; the results are shown in TABLE 6.

TABLE 6 The results of the Type 3 test of Fixed Effects. The dependent variable was PA, and a statistically significant significance (*) is indicated when $p < \alpha$ ($\alpha = 0.05$).

Source	Numerator df	Denominator df	F	p
ASDvsNeurotypical	1	16.97	13.28	0.002*
ExecutionType	1	88.12	51.09	0.000*
CueType	2	88.10	1.30	0.278
ASDvsNeurotypical* CueType	2	88.10	0.45	0.637

In order to confirm that significant effects that are observed in TABLE 6 were seen across all features, the same test was performed across the other features (NS1, NS2, and RR). For these tests, only the significant effects are investigated. Thus, the two-way interaction between ASD and cue type is ignored for the other features. TABLE 7 shows the results of the Type 3 test of Fixed Effects. The effect observed from ASD shows a significant difference across all features. The movement execution type (real movement vs. imagined movement) also had a significant effect on all features except for NS2.

TABLE 7 The results of the Type 3 test of Fixed Effects in which the response variable was changed to be the other features NS1, NS2, and RR. Significance (*) is indicated when $p < 0.05$.

Source, with NS1 as response variable	**Numerator df**	**Denominator df**	**F**	**p**
ASDvsNeurotypical	1	16.47	17.67	0.001*
ExecutionType	1	87.69	5.96	0.017*
Source, with NS2 as response variable	**Numerator df**	**Denominator df**	**F**	**p**
ASDvsNeurotypical	1	16.96	3.28	0.088
ExecutionType	1	88.07	45.88	0.000*
Source, with RR as response variable	**Numerator df**	**Denominator df**	**F**	**p**
ASDvsNeurotypical	1	17.07	8.35	0.010*
ExecutionType	1	88.18	80.31	0.000*

3.2.2 Power Analysis and Sample Size Estimation

To determine the effect size of ASD on MRCP features, Cohen's *d* was calculated for each of the four MRCP features. TABLE 8 reports the effect size that ASD has on each feature of the dataset. The data has been split between imagined and real movement execution type. The data of the three interface cue types have been grouped together since they were shown to not have any significant differences in TABLE 6. Using Cohen's guidelines for determining effect sizes, ASD has medium and almost large effects in both real and imagined movement execution for features NS1 and PA [74].

TABLE 8 The measurements of effect size using Cohen's d for each of the MRCP features. Large effects are considered to be d > 0.8 and medium effects are when d > 0.5 [74].

Movement Execution Type	**Effect Size of ASD on MRCP Features**			
	NS1 (μV/s)	**NS2** (μV/s)	**PA** (μV)	**RR** (μV/s)
Real Movement	0.6952	0.4509	0.6137	-0.4392
Imagined Movement	0.7159	0.4830	0.7489	-0.7107

A power analysis was conducted on the study presented to determine how likely it is to identify statistically significant differences between an ASD and neurotypical group should they exist in a larger population. Because PA is a highly representative feature of MRCPs and have large effect sizes they are used as the critical difference used for the power analyses. To conduct the power analysis for each movement type, the pooled standard deviations of the real and imagined PA features and $\alpha = 0.05$ are used. Given our collected sample size of 10 pairs, our study only has a power of $\beta = 0.03$ for real movement execution and $\beta = 0.02$ for imagined movement execution. Under the same conditions, the minimum sample size needed to achieve sufficient

power ($\beta >= 0.80$) for this observed effect is 1018 pairs of participants for real movement execution and 395 pairs of participants for imagined movement execution.

3.2.3 MRCP Detection rate using LPPs

As a post-hoc analysis, MRCP detection using LPP was processed using the data for each participant to predict performance and the time of detection. The performance is measured by the number of true positive detections and determined whether the participant's MRCP is differentiable enough from the noise to be applied to a BCI. The time of detection will indicate whether MRCP is detected soon enough to achieve Hebbian plasticity for neurorehabilitation (as discussed in section 1.5).

Two sets of data were used to create the LPP machine-learning classifier. The machine learning model was trained and tested on each individual participant. The training data set was the auditory interface using real movement for a participant, and the testing data set was the visual interface using real movement for the same participant. The haptic interfaces were not used for MRCP detection because the full data set was not available for all participants. Since the statistical analysis in TABLE 6 indicated that there is no statistically significant difference between interfaces, the selection of auditory and visual interface data for training/testing is not relevant.

To train the model, a sliding window of two seconds long was used across the Laplacian-filtered data corresponding to the electrode channel Cz. The window slid in steps of 50 ms (60 samples given 1200 samples per second collected. Feature extraction was performed using LPP, and then labelled based on whether an MRCP event was occurring or not. The label was determined using movement onset detected in the EMG, where the window would be labelled as MRCP-detected data if the window locates completely between two seconds before to two seconds after movement onset. Thus the EEG data labelled as non-MRCP occurred between 2 second to 6 seconds after movement onset and windows outside of those periods were ignored. The features extracted with LPP are used to train a linear discriminant analysis (LDA) model, which fits a linear

boundary between LPP features that represent an MRCP-detected event and no MRCP event. This boundary is used to make future predictions on future EEG data, based on what side of the boundary the LPP features are on.

Then the model was tested on an unseen set of data (i.e., the real movement interface with visual cues). A window of the same size as the training data was moved along the filtered EEG data across time. Each window of incoming data was processed with LPP, and then fed to the LDA classifier to predict if MRCP has occurred. If the classifier predicted the MRCP had indeed occurred, then the window was validated against the EMG-aligned data of that particular epoch. If MRCP was occurring in the epoch, then a true positive was detected. If not, then a false positive had occurred. This continues until the window moves until there is not enough EEG data to populate an entire window of data. Then, the true positive rate and false positive rate is measured based on the number of correct and incorrect MRCP detections.

The number of true positives represent how many MRCP events were within ±2 seconds within the go cue. Once a true positive is detected, the time of detection with respect to movement onset in the EMG is recorded and then the next trial is processed. Since there are 20 “go” cues in each testing set, the number of true positives can be any integer between 0-20. False positives were ignored as the ASD subjects often shuffled or moved in their seat during the rest period between cues, and thus are a factor of restlessness of the participant instead of the success of the algorithm. TABLE 9 represents the results of MRCP detection results. As indicated above, a set of training and testing data are required to perform the detection algorithm. Since the interfaces were found to not be statistically significant (see TABLE 6), the visual interface sessions were used as training data, and the auditory interfaces were chosen as testing data. Haptic interfaces were not chosen for MRCP detection because two neurotypical subjects had their haptic interface with real movement

execution data rejected. The auditory and visual data was complete across all subjects, so they were used instead.

TABLE 9 MRCP Detection results for neurotypical (s) and ASD (AS) subjects. The mean detection time represents when the events were detected prior/after the event (positive numbers indicate the event was detected after the go cue; negative numbers indicate prior to the go cue).

Participant	Real or imagined movement	Number of true positives	Mean detection time before movement onset
S02	Real	6	-251 ms
	Imagined	7	-87 ms
S03	Real	11	358 ms
	Imagined	4	-4 ms
S04	Real	11	-202 ms
	Imagined	6	-35 ms
S05	Real	11	-86 ms
	Imagined	10	-250 ms
S08	Real	6	494 ms
	Imagined	4	353 ms
S09	Real	6	11 ms
	Imagined	7	66 ms
S10	Real	10	312 ms
	Imagined	1	-587 ms
S11	Real	5	-231 ms
	Imagined	6	-6 ms
S14	Real	7	-18 ms
	Imagined	6	206 ms
S15	Real	12	-17 ms
	Imagined	10	-172 ms
AS01	Real	14	192 ms
	Imagined	11	-105 ms
AS02	Real	5	521 ms
	Imagined	9	0 ms
AS03	Real	2	8 ms

	Imagined	7	356 ms
AS04	Real	0	-
	Imagined	5	376 ms
AS05	Real	8	-157 ms
	Imagined	10	2 ms
AS06	Real	4	-477 ms
	Imagined	7	-37 ms
AS07	Real	2	873 ms
	Imagined	3	153 ms
AS08	Real	3	-380 ms
	Imagined	4	-18 ms
AS09	Real	5	-450 ms
	Imagined	11	77 ms
AS10	Real	5	33 ms
	Imagined	7	-266 ms
Mean (ASD)	**Real**	4.8	16.3 ms
	Imagined	7.4	53.8 ms
Mean (Neurotypical)	**Real**	8.5	37 ms
	Imagined	6.1	-51.6 ms

3.3 Analysis of Qualitative Surveys

The qualitative analysis focuses on the survey data and reported preference rankings of the three different interfaces (auditory, haptic, visual). The overall response rate of completed surveys was 64%. However, some participant data was rejected from the quantitative analysis (discussed in section 3.1) and thus cannot be used for the qualitative analysis. The complete response rate was 75% for the rest of the participants. Details about the second question have been omitted in this section since they were optional to fill in but can be found in TABLE 13 in the Appendix. A full systematic qualitative analysis was deemed to be unnecessary for the scope and maturity of this research, therefore a high-level descriptive qualitative analysis was conducted.

3.3.1 Interface preference ranking

The mode of the rankings was measured to see which ranking an interface was most often indicated as. The reported preference rankings are can be seen in TABLE 9. AS01, and S02-S05 did not report their ranking and thus are not included in the table below. S12 and S13 reported their rankings, but their EEG data was rejected due to poor signal quality. As a result, their qualitative results have also been omitted from TABLE 9.

TABLE 9 Preference rankings for different cueing modalities as reported by the participants where 1 = most preferred and 3 = least preferred. Two numbers in the mean indicate that those rankings were the mode (i.e., the interface was the most often ranked both of the numbers indicated).

Participant	Real Movement			Imaginary Movement		
	Auditory	Visual	Haptic	Auditory	Visual	Haptic
S08	3	2	1	1	2	3
S09	1	2	3	3	2	1
S10	3	2	1	3	2	1
S11	2	1	3	2	1	3
S14	2	1	3	1	2	3
S15	3	1	2	3	2	1
AS02	2	3	1	2	3	1
AS03	1	3	2	1	2	3
AS04	1	2	3	2	3	1
AS05	2	1	3	2	3	1
AS06	2	3	1	3	2	1
AS07	2	1	3	1	2	3
AS08	1	2	3	3	2	1
AS09	2	3	1	2	3	1
AS10	1	3	2	2	3	1
Mode (all participants)	2	-	3	2	2	1
Mode (ASD)	2	3	3	2	3	1

Mode (Neurotypical)	3	1, 2	3	3	2	1, 3

To compare what participants' self-reported preferred interface was to the interface that elicited the best MRCP, data from TABLE 9 was compared with the interface that elicited the strongest MRCP (indicated by having the lowest PA value) as selected in TABLE 14 in the Appendix. Some participants were omitted from this comparison as they did not report their rankings in TABLE 9. The haptic, real-movement execution run in S15 was also rejected due to the presence of too much noise, therefore their best performing real-movement interface cannot be reported on. The comparison of performance based on MRCP data and subjective ranking by participants can be found in TABLE 10.

TABLE 10 Comparison between the participants' subjective ranking of interfaces with the MRCP data. Dashes indicate that there is no mean available for that group.

Participant	Best Subjective Real Movement Interface	Best MRCP Real Movement Interface	Best Subjective Imaginary Movement Interface	Best MRCP Imaginary Movement Interface
S08	Haptic	Haptic	Auditory	Auditory
S09	Auditory	Haptic	Haptic	Visual
S10	Haptic	Haptic	Haptic	Haptic
S11	Visual	Haptic	Visual	Visual
S14	Visual	Visual	Auditory	Auditory
S15	Visual	-	Haptic	Haptic
AS02	Haptic	Auditory	Haptic	Haptic
AS03	Auditory	Auditory	Auditory	Haptic
AS04	Auditory	Visual	Haptic	Haptic
AS05	Visual	Visual	Haptic	Haptic
AS06	Haptic	Haptic	Haptic	Visual
AS07	Visual	Auditory	Auditory	Haptic

AS08	Auditory	Visual	Haptic	Haptic
AS09	Haptic	Haptic	Haptic	Haptic
AS10	Auditory	Auditory	Haptic	Visual
Mean (ASD)	Auditory	Auditory	Haptic	Haptic
Mean (Neurotypical)	Visual	Haptic	Haptic	-

3.3.2 Survey results

TABLE 11 shows the responses of the Likert rankings about the likability of the interface from question 1 of the survey. The question asked was "On the scale to your right, please indicate how you felt when interacting with that type of interface." This question had a 100% response rate for all subjects.

TABLE 11 Responses from question 1. Responses are represented as an integer from 1-5, where 5 = Very pleasant and 1 = Very unpleasant.

Subject	Real Movement			Imaginary Movement		
	Auditory	Visual	Haptic	Auditory	Visual	Haptic
S02	5	4	5	4	3	4
S03	3	2	5	4	2	5
S04	5	4	4	5	4	4
S05	5	4	5	2	3	3
S08	3	4	5	3	3	2
S09	5	4	2	5	4	5
S10	3	3	4	3	3	3
S11	5	5	5	5	5	5
S14	3	4	2	4	3	2
S15	2	4	3	4	5	5
AS01	5	5	5	5	4	4
AS02	3	3	5	3	2	3
AS03	5	5	5	5	5	5
AS04	5	4	4	5	4	5
AS05	4	5	3	5	5	2
AS06	4	5	5	3	3	3
AS07	3	4	3	3	3	2
AS08	5	3	3	5	3	2
AS09	4	4	4	3	3	4
AS10	4	3	3	4	3	3

Mean (all participants)	4.05	3.95	4	4	3.5	3.55
Mean (ASD)	4.2	4.1	4	4.1	3.5	3.3
Mean (Neurot-ypical)	3.9	3.8	4	3.8	3.5	3.8

Responses from the second question "Please tell us a little bit more about why you feel this way" are available in TABLE 13 of the Appendix. Because it was an optional open-ended question, not every participant wrote a response. Examples of data from Question 2 are presented in section 4.4 to provide context to the results.

The third question "In your opinion, would you feel comfortable using this type of system to control a machine or computer?" was a general usability question and was captured as a binary response (i.e., 'yes' or 'no'). The response rate for this question was 100% and are shown in TABLE 12.

TABLE 12 Responses from question 3 in the survey where 1 = "Yes" and 0 = "No."

Participant	**Real Movement**			**Imaginary Movement**		
	Auditory	**Visual**	**Haptic**	**Auditory**	**Visual**	**Haptic**
S02	1	1	1	1	0	1
S03	0	0	1	1	0	1
S04	1	1	1	1	1	1
S05	1	1	1	0	0	0

S08	1	1	1	1	1	0
S09	1	1	1	1	1	1
S10	1	1	1	0	0	1
S11	1	1	1	1	1	1
S14	1	1	1	1	0	0
S15	0	1	0	1	1	1
AS01	1	1	1	1	1	1
AS02	1	0	1	1	0	0
AS03	1	1	1	1	1	1
AS04	1	1	1	1	1	1
AS05	1	1	1	1	1	0
AS06	1	1	1	1	1	1
AS07	0	1	0	1	0	0
AS08	1	1	0	1	1	1
AS09	1	1	1	1	1	1
AS10	1	1	1	1	1	1
Mean (all participants)	0.85	0.9	0.85	0.9	0.65	0.7
Mean (ASD)	0.9	0.9	0.8	1	0.8	0.7
Mean (Neurotypical)	0.8	0.9	0.9	0.8	0.5	0.7
95% Confidence Interval	0.6311 to 0.9561	0.6867 to 0.9843	0.6311 to 0.9561	0.6867 to 0.9843	0.4316 to 0.8201	0.4787 to 0.8548

4. Discussion

4.1 Summary of key findings

From the results, we have established the following key findings:

1. There are statistically significant differences in MRCP features between the neurotypical and ASD groups.
2. There are no statistically significant differences between MRCPs generated with different interface types (haptic, auditory, visual) across both groups of participants.
3. The type of interface that is preferred by subjects is not often the interface that elicits the strongest MRCP features.
4. The ASD group has less false positive events and more true positive events in imagined movement trials in MRCP detection compared to the neurotypical group.
5. Haptic interfaces were most often ranked as the most preferred interface for imagined movement BCIs in both groups.
6. Auditory interfaces were reported as being the most pleasant interface in the imagined and real-movement BCIs in both groups.

4.2 Case Study Discussion

Several findings from the statistical analysis presented in 3.2.1 are clearly seen in the case study presented in section 3.1.1. The first finding that is evident from the case study is that the features in the ASD participant are much smaller in magnitude than the neurotypical participant. This is supported with the Type 3 test of Fixed Effects and the side-by-side comparison in TABLE 5.

A second observation from the case study is that that the rebound rate after movement execution surpasses the baseline potential. The baseline can be observed between 4-3 seconds prior to movement execution in TABLE 5. The rebound rate is believed to reflect the fine control of movement and reafferent sensory processing that results from the participant moving their foot [75]. Although the observed overshooting of the baseline may indicate some interesting activity for ASD participants, it was not observed in all participants in the ASD group. The observed overshooting may be related to hypersensitivity experienced by these ASD participants, but further work is needed to investigate how often this occurs.

A third observation is that the ASD participant has less inter-trial variation in their EEG features than the neurotypical control. The neurotypical participant has high inter-trial variability but elicits more pronounced features. One might infer from the third observation that MRCP detection will be improved in neurotypical participants, since the features are more distinctive and thus 'easier to detect.' However, this decrease in variation does not indicate necessarily that MRCP detection is more difficult because in section 3.1.1, it was observed that the EEG seemed to vary less in amplitude over time in in the ASD participant. Thus, even small changes can still be significant enough for successful MRCP detection. TABLE 9 shows that the average MRCP detection is very similar between the ASD and neurotypical groups. The most important factor for

reliable MRCP detection is a strong SNR; namely, whether there are little or large amounts of noise in the EEG, the signal needs to be prominent enough to be detected. Thus, having more pronounced features won't necessarily impact how well MRCP can be detected in that subject.

4.3 Quantitative Data

Originally, the target size for both groups was 12 participants. While the target size of 12 participants was not met, the sample size of 10 participants for each group is similar to comparable studies such as [28], [76], and [77].

The results of the Type 3 test of Fixed Effects in TABLE 6 reveals statistically significant differences across movement execution (real or imagined movement) and the participant groups (neurotypical and ASD). The significance of movement execution type is not a surprise; it has been well-documented in research literature over several decades that real movement execution produces more pronounced MRCPs than imagined movement does [78]. It has been presented to validate the dataset collected and thus will not be discussed further. The Type 3 test of Fixed Effects also demonstrated that the interface cue type (visual, auditory, haptic) appears to have no significant effects on MRCP features. This is relevant to the first research question presented in this thesis, "What is the quantitative EEG response of people with ASD to different BCI sensory modalities (auditory, haptic, visual) with their EEG?" While there is no statistically significant response in the participants' EEG data, the qualitative results provide interesting insights on the subjective differences in the interface cues discussed in section 4.4.

The most significant finding was the statistically significant differences in MRCP features between the neurotypical and ASD groups. The difference is also clear in the side-by-side comparison in FIGURE 8. The neurotypical group has larger values in every feature, and this observation is consistent between real and imagined movement execution. The peak amplitude of negativity is much smaller in value in the ASD group than the neurotypical group, which provides insights into how the brain is preparing for movement. As stated in section 1.5, the potentials of MRCP are related to the amount of neurons being recruited for the movement task. The more

neurons that are being recruited to prepare for movement execution, the lower that the peak amplitude will be for MRCP, which in turn affects all the other feature values as well. This suggests that less neurons are recruited for movement task intention and preparation in the ASD group compared to the neurotypical group, and thus less activity occurs. This is significant for the research questions presented in this thesis because it resolves the third question, "Do movement-related cortical potentials differ in people with ASD, compared to a neurotypical population?" MRCP features indeed differ between the two groups, and this difference has consequences on cortical activity for preparing and executing motor tasks.

The effect size in TABLE 8 demonstrates that the effect ASD has on these features is not small. Using Cohen's criteria, the measurements of effect sizes are considered medium, trending toward large [74]. However, this effect size is tempered by having an underpowered study. While this study was an important pilot to demonstrate the effect of ASD on MRCPs, the small sample size means that it is underpowered and thus prone to Type II statistical errors. The power analysis in section 3.2.2 means that at least 1018 participants in each group are needed to have a sufficiently-powered study such that we could predict how this effect behaves in a more general population. This would be an important step to demonstrate MRCP differences in a more general population before developing or commercializing technology that could solve this. The limitations in such a study is discussed in section 5.

Although the ASD group was unable to elicit an MRCP response as prominent as the neurotypical group, this does not mean that they are unable to perform motor tasks correctly. Rather, it suggests that the cognitive processing involved during motor task preparation in the ASD population is not as predictable as the neurotypical population. This could be related to difficulties with executing fine motor tasks such as coordinating movements to a cue, which is a common

occurrence in people with ASD. Because MRCPs are generated during voluntary movement planning, this may indicate that among ASD population there is a deficiency in planning movement tasks effectively. Existing BCI research for ASD has only focused on EEG signals related during or after motor tasks, with many results proving to be inconclusive or contradictory to other studies [79], [28], [80]. Thus, different MRCP morphology in ASD may be related to why people with ASD have issues with fine motor tasks, since the different MRCP morphology could indicate different neuronal activation patterns with motor movement planning as well as the motor execution as already identified in the research. Movement planning also lies under executive functioning, which is a difficulty in people with ASD. Thus, MRCP may be reflective of motor control as well as executive functioning abnormalities in ASD. Thus, improving MRCP elicitation may lead to improvement in motor and executive functioning abnormalities in those with ASD. More research is needed to focus on this component but may have a significant impact on the ASD community.

This finding is particularly significant with current ASD research. Since an abnormal MNS system has already been proposed in prior research investigating *mu* rhythms, the research presented in this thesis suggests that *mu* rhythms and its role in the MNS is not sufficient for describing the symptoms experienced by those with ASD. MRCPs are generated in the same location of the brain as *mu* rhythms and show an abnormal elicitation in the ASD participants, as demonstrated by TABLE 6 and TABLE 7. As MRCPs are generated prior to *mu* rhythms, the inability of a person to elicit proper movement intentions could lead to abnormal cognitive processing of the movement itself, and consequently abnormally suppressed *mu* rhythms. Abnormal MRCPs could also be a result of less connections between neurons available, leading to more difficulty in recruiting neurons to participate in tasks. Regardless, abnormal MRCPs imply

that there is likely more happening in intentionally generated EEG signals for ASD than current research suggests.

Differences between the neurotypical and ASD groups also exist with MRCP detection success. In TABLE 9, the neurotypical group had more true positives than the group with ASD and the mean detection latency was shorter and earlier than the ASD group in imagined movement. Thus, more MRCP events can be identified earlier in the neurotypical group compared to the ASD group for imagined movement. The lower true positive rate in real movement as well as the poor detection time of MRCP in ASD is likely due to their less pronounced MRCP components compared to the neurotypical group. Since LPPs rely on spatial relationships in the EEG, signals that do not spatially separate themselves from EEG noise will not be detected as easily. Despite this, the mean detection times in both real and imagined movement execution in the ASD group had an average detection latency within 200 ms after the "go" cue. As a result, this algorithm can detect their intentions within the window needed for perceived real-time feedback and can achieve Hebbian learning.

As demonstrated in TABLE 6 and TABLE 7, MRCP differences between the neurotypical and ASD groups exist. Thus, the ASD population may benefit from MRCP-based neurofeedback to improve activation in the motor cortex. In using MRCP for neurofeedback, we can achieve Hebbian learning (see section 1.5) and strengthen the cortical activation of the primary motor cortex, which can potentially enable improvement in the activation of the MNS. While this has not been demonstrated yet, future research can explore if MRCP training can indeed improve MNS function. Improvements with stroke and Parkinson's patients have already been put in place by using neurofeedback with MRCP [60], [81], [82]. Since there are similarities between the poor motor control between these populations and ASD, it is worthwhile to explore if neurofeedback

using MRCPs can improve motor functioning. However, more research needs to be done to see how consistent neurofeedback will be across ASD populations in order to justify such type of systems (as explained in section 1.3).

4.4 Qualitative Survey Data

The Type 3 test of Fixed Effects demonstrates that the interface cue type (visual, auditory, haptic) appears to have no significant effects on MRCP features. However, the qualitative results provide interesting insights on the subjective differences in the interface cues, especially when considered in parallel with related quantitative data. Even though no statistically significant differences were found in the MRCP features between interfaces, the questionnaire data appears to identify some polarizing opinions about different interfaces. This was especially apparent in ASD survey responses. For example, for subjects AS07 and AS08, the haptic interfaces were likened to 'shock collars.' One wrote it down, and another reported this verbally. Such language is very polarized and frames haptic interfaces as dangerous and pain-provoking. It should be noted that the vibration was at the same frequency for all participants and the haptic wristband was reported to be comfortable verbally by each participant before every haptic interface test was done. While the other participants were not bothered by the haptic interfaces, 20% of the ASD participants is enough to indicate that haptic interfaces should not be the standard, especially since using other interfaces does not appear to affect MRCP morphology. While some other participants self-reported hypersensitivities to the other interface stimuli, they did not use language that would suggest suffering or perceiving pain in any capacity.

This negative feedback for the haptic interfaces is reflected in those participants' Likert scores, which were lower than the other interfaces. However, their EEG data showed that the haptic interfaces performed the best for both these participants. If BCI interface were chosen based on quantitative data alone, it would neglect how participants feel about the BCI interface, which could jeopardize the acceptance, usability, and uptake of BCI for people with ASD. Thus, it is very important for researchers and developers of BCIs to include some form of qualitative data to investigate subjective opinions regarding designs.

As discussed at the start of section 4.3, it was identified that there are no significant differences between the auditory, haptic, and visual interfaces. Prior work by Pearce et al. found that auditory and visual interfaces had no statistically significant effect on MRCP responses in neurotypical participants, which is validated by the work presented in this thesis [83]. Given that many people with ASD report a hypersensitivity to stimuli, it is yet to be determined whether hypersensitivities would impact the elicitation of MRCP responses. Three ASD participants self-reported their hypersensitivities either verbally or written down in question 2 of the survey. It may be assumed that the hypersensitivities would lead to non-optimal performances in the respective interface; however, the interfaces that these three participants sensitive to ended up being the best performing in terms of MRCP peak amplitudes of negativity. Thus, it is not possible to identify this effect only using EEG. This is problematic if researchers and developers focus on creating interfaces that generate optimal MRCP signals in order to achieve as high classification accuracy as possible, as they may effectively design interfaces that people wouldn't want to use. Preferences for interaction modalities for people with ASD can be quite strong, as supported by qualitative responses for this research. These preferences will have a larger impact on BCIs than the insignificantly small changes in the EEG data. Thus, the data from this work suggests that selecting

an interface based on quantitative EEG data alone is inappropriate and could be detrimental to the adoption of the BCI for ASD populations. Others should be weary of relying on quantitative data alone, as it may not indicate usability issues that will deter the success of BCIs in a commercial setting.

Based on the Likert responses for question 1 in TABLE 11, the BCIs that used imagined task execution are perceived as less pleasant than BCIs with real movement tasks. This finding is not surprising as it is more difficult to perform an imagined task, and imaginary tasks tends to cause mental fatigue in many people [84]. The mean Likert scores for real-movement interfaces indicate that visual and auditory interfaces are rated higher than the haptic interface across all participants and the ASD group, but the neurotypical group prefer the haptic interface most. For imagined movement interfaces, the auditory interface is the highest rated across all groups. The visual interface has the lowest score across all participants and within the neurotypical group, and in the ASD group the haptic interface is scored lowest. On average, it appears that haptic interfaces are better for neurotypical populations than for ASD. Haptic interfaces are perceived poorly compared to the other two interfaces for the ASD group. This is significant to the second research question presented in this thesis, “How do people with ASD subjectively perceive their interaction with auditory, haptic, and visual sensory stimulation?” because it indicates that haptic interfaces should be avoided for BCI design for ASD populations. For neurotypical populations, haptic interfaces are perceived better compared to the other two interfaces. Based on the highest rated scored in the ASD group, auditory interfaces may be more appropriate. However, these findings should only be used a starting point for BCI development and research. Factors such as hypersensitivities should be strongly considered and will have a large impact on the perception of the BCI.

In the reported rankings of real-movement interfaces (see TABLE 9), the auditory cues were most often ranked as the most preferred choice overall, and the neurotypical group most often chose visual interfaces as the highest ranked interface. All groups most often chose haptic interfaces as the least preferred interface. While the interface that was often ranked highest aligns with the observations in the Likert responses with the real-movement interfaces (see TABLE 11) this was not the case for imagined movement BCIs. In the imagined movement interfaces, the haptic interface is usually ranked the most preferred interface across all groups, while the Likert scores suggest that auditory interfaces are the most preferred. There is an inconsistency present here, which indicates some biases that come in self-reporting right after interacting with the interface. When participants are asked to rate an interface without having experienced all three interfaces, opinions are likely to change after working with all the interfaces. While ranking may appear to be more appropriate for comparing several interfaces, there is a lack of qualitative data in justifying *why* participants feel a particular way. Rankings are also unable to capture the impulsive, initial feelings of the perception of the BCI. The first impression of a BCI is recorded in the post-task Likert scales because the participant reports this immediately after interacting with the BCI. Thus, the post-task Likert scales can provide more insight to the first impressions, and the participant can justify why those feelings are present in an open-ended question like question 2.

From the data collected in this research, it appears that the ranking method provided more insight as to what interface would be best out of a set of options compared to the Likert scales. The Likert scales were often filled in with the same rating across all interfaces, unless the participant indicated a dislike of an interface (and thus marked a very low on the Likert scale for that interface). This does not give good insight as to what interfaces are best, as it only indicates poor interfaces.

This is particularly relevant for A/B testing for research and development because users will report lower results for the one they don't like. Likert scales are less valuable when there are more than two interfaces to assess because the same rating will likely be filled in for several interfaces, and thus it is difficult to identify differences in preferences between them. Thus, it is recommended that BCI research and development use rankings rather than Likert scales to determine most preferred interfaces, since the Likert scores were not always definitive in comparing interface designs and were positively skewed.

In this comparison between the subjective rankings from TABLE 9 and the Likert scale responses from TABLE 11, it appears that for simple product validation that does not require a deep-dive into why BCI users feel a way, rankings are more appropriate than Likert scales. When justification is required, using the Likert scales and open-ended questions are more appropriate. Even though the rankings and Likert scale data may contradict each other, we have demonstrated that the ranking and Likert scales are equally important because they provide interesting and capture different contexts.

When the subjective rankings are compared with MRCP data in TABLE 10, 66% of the subjects reported preferences for interfaces (either real or imagined movement execution) that did not reflect that they performed the best in. Out of the interfaces using real movement execution, 43% of subjects preferred interfaces that were not their best performing. For the imagined movement execution, only 33% of subjects preferred interfaces that were not their best performing. This misalignment is important to the second research question presented in this thesis because the preferences of the participants discussed above that answer this question would rarely be selected as the best interface to be used in research. Because BCI researchers are looking for methods to get the best results, there will be a bias towards using interfaces that yield the best signals.

However, the interface with the best signals rarely align with what would be most preferred by the participants. While using the interface with the best signals aligns with research, the BCI is less likely to be adopted in a commercial setting if people are less likely to use it. If people aren't going to use the interface then there is little worth in the research and development of those BCIs, especially when BCIs are designed for commercial use.

Because imagined movement BCIs are harder to use than real movement BCIs, it was not a surprise when imagined movement BCIs were rated lower than the real-movement counterparts. This is seen in overall, and in the ASD and neurotypical groups. While this difference does exist, the perceived usability of the interface was not significantly different even when considering this observation. Thus, the different types of interfaces appear to have strong preferences by the participants, which will affect the success and adoption of that BCI. Whether the interface uses real or imagined movement does not significantly impact these perceptions. These perceptions are also not reflected in the quantitative data, which again supports the importance of capturing qualitative data when developing BCIs. It is recommended that future BCI work should include qualitative surveys to capture a more holistic understanding of the BCI system. Otherwise, BCIs may not be successfully translated into real-world applications and commercially viable systems.

The third question in the survey use the binary responses to predict the usability rate, and the confidence interval suggests that there is a 95% level of confidence that about 63-98% of the general population would perceive real movement BCIs as usable, and about 43-98% for imagined movement interfaces. Thus, the binary usability responses from TABLE 12 show promise for the future of BCI technologies. The responses were mostly positive and indicate there exists at least some fraction of the population that sees the value of using BCIs in their lives. The adjusted confidence intervals in TABLE 12 show that it is possible that the population will also see value

in MRCP-controlled BCIs when they are more widespread and commercially available. The responses demonstrate that MRCP interfaces could be a viable commercial solution that the general population would be likely to try. However, it should be noted that this does not indicate whether they would continue to be used over a long enough period of time to achieve the benefits of using such BCIs. This may also be affected by the excitement new technology often incites in early-adopters of innovative technology. It is important that long-term studies on BCI use are conducted to examine whether consumers would use BCIs consistently.

In TABLE 13 of the Appendix, the responses from question 2 of the survey are recorded. While each person had personal opinions about the interfaces (and MRCP-based BCI technology overall), there were some common topics or language used that can provide rich qualitative insight into the experiences of participants when using different MRCP-based BCIs. First, 8 neurotypical and 3 ASD participants self-assessed their ability interacting with the BCI based on how distracted they were. While the details of how distracting the cue stimulus was varied, there were some repeated patterns that indicates potential problems when moving such BCIs to market.

Another useful finding from these responses was that several participants liked non-visual interfaces because they did not need to attend to the stimuli. Visual cues require more sustained attention to a screen than other interfaces, which can hinder multitasking when using BCIs. If BCIs are used for communication or control, the need to constantly attend visual stimuli should be avoided to allow people to engage more with their environment around them while they use it.

In the experimental paradigm outlined in this study, neurofeedback was not incorporated or presented to the user. One participant wrote down feelings of frustration for not being able to receive feedback on their performance. Three participants expressed these feelings verbally; one in the neurotypical group, and two in the ASD group. Neurofeedback was not included because

participants may assess an interface on their perceived performance based solely on neurofeedback, rather than assessing the BCI based on their own interpretations of cue types. However, the importance of including such feedback is a critical step in determining whether a BCI user is improving or needs to change a specific behavior.

4.5 Peroration

Given these observations, there are new questions that should be asked by BCI researchers and developers. First, a logical next step is to investigate how BCI preferences compare with other EEG signal modalities. For some types of modalities, it may be that one type of interface may be strongly preferred over another; there may be interesting results for interfaces involving other movement or sensory-based brainwaves. Second, it is not yet clear as to whether the neural circuits that yield abnormal MRCP elicitation contribute to what causes ASD (or how the symptoms persist) or are merely a consequence of other abnormally functioning systems such as the MNS. While there is not enough data from this work to tell, it can be said that current EEG research on ASD has been focused on specific brainwaves that may not represent how ASD persists in EEG and that there may be than the MNS that is abnormally functioning in those with ASD. Such questions need to be asked in order to develop appropriate treatments and therapy for those with ASD.

The results show that there is a difference in MRCP elicitation between the ASD and neurotypical groups. Improvements with stroke and Parkinson's patients have already been put in place by using neurofeedback with MRCP [60], [81], [82]. Since there are similarities between the poor motor control between these populations and ASD, it is worthwhile to explore if neurofeedback using MRCPs can improve motor functioning. However, more research needs to be done to see how consistent neurofeedback will be across ASD populations in order to justify such type of systems (as explained in section 1.4).

Qualitative data provides important insights that would have been unidentified if only EEG data was used for analysis. It is recommended that more qualitative data is considered when researching and developing BCIs. When researchers capture and qualitative data on the

participant's preferences, it creates active engagement with the users and gives them a say in the development. This empowers BCI users and fosters a positive relationship between technology and users. All the incredible work done by academia in BCI falls apart if the people it is designed for can't or won't use it. In the end, it all comes back to "nothing about us without us."

5. Methodological Considerations

There are three considerations this thesis considers. First, this research had small sample sizes, which is common in early-stage BCI research. Due to the small sample size, we cannot conclude for certain that the data presented in this work is representative of larger populations. In order to have sufficient statistical power, the power analysis in section 3.2.2 estimates a minimum sample size of 1018 participants for each group. It is very rare to see BCI studies that recruit such a high number of participants for a number of reasons. Depending on a variety of factors such as geography and local demographics, there may be few people that meet the special criteria for BCI investigations. Furthermore, the equipment needed to conduct BCI studies is expensive and not portable. Participants often must travel to the institution which can be overbearing and time-consuming for participants. While there may be sufficient neurotypical participants, it is highly unlikely that the same number of ASD participants can be recruited. As discussed in section 2.1,the sample sizes collected for this study is consistent with other BCI studies, most of which is developed and designed for special needs populations. While it is acknowledged in the academic research fields that this is a major problem in BCI research, there are currently few solutions available for this problem. Solving these problems are outside of the scope of this thesis.

The second consideration is that the MRCP detection algorithm used is not a generalizable model. Because there is high variability in MRCP features based on the subject, and the locality preserved projections have different feature the detection algorithm is built specifically to the morphology of the subject's EEG data. As a result, the models used for MRCP detection on one participant will not be generalizable to other participants. If one participant is very good at eliciting MRCP, it is unlikely to work as well on other subjects. Unfortunately, it means that the detection models developed and tested for this thesis cannot be used in. commercial device at this time.

Lastly, while the results presented in this work demonstrated a difference in MRCPs between neurotypical and ASD participants, it is yet to be determined whether neurofeedback using MRCPs is due to an abnormal MNS or can improve MNS functionality. While *mu* rhythms and MRCPs both engage similar motor systems, there are currently no studies to empirically prove this link between MRCP and the MNS. Furthermore, MNS is still a theory at this point and researchers are still unsure whether there is enough support to prove that the MNS exists in humans. if there is enough evidence to support its existence.

6. Conclusions and Recommendations

6.1 Conclusions

The goal of this thesis was to answer the research questions:

1. What is the quantitative EEG response of people with ASD to auditory, haptic, and visual BCI sensory modalities?
2. How do people with ASD subjectively perceive their interaction with auditory, haptic, and visual sensory stimulation?
3. How do movement-related cortical potentials compare between people with ASD and neurotypical controls?

For question 1, no statistically significant differences were found in MRCP features between auditory, haptic, or visual-based BCIs. The data also demonstrated peak amplitudes that were smaller in value between the ASD compared to neurotypical groups, suggesting that MRCPs differ between the two populations, which relates to question 3. For question 2, the qualitative data demonstrated ASD group perceived differences in BCI modalities such as preferences based on stimuli hypersensitivities, incompatibilities between participant's preferred and best performing interfaces, and the benefits of using interfaces that don't require constant visual attention.

The work presented today provides several novel contributions to the current body of research. In thus study, the first comparison of MRCPs between ASD and neurotypical populations are presented. This comparison included EEG and a qualitative perception of the different interfaces, which presents a more comprehensive comparison than other research in this area, which only examines the EEG signals. Furthermore, this is the first study to examine the

differences between haptic, auditory, *and* visual responses in MRCP elicitation in any population between different interface cues.

6.2 Recommendations

There were several polarized opinions expressed by participants about the interfaces based on prior experiences and sensitivities. Because haptic interfaces were so polarized (and potentially perceived as harmful to those with ASD) and visual interfaces were a little distracting, it may be best to use auditory cues for early stage development of MRCP-based BCIs. This finding can be expanded to other BCIs, as the reasoning for preferring one interface for another was not often due to its relation to the task. However, it is important to recognize the limitations of auditory MRCP-based BCIs based on the audience the BCI is being developed for. Auditory cues are a good place to start at the beginning but may need to be enhanced or used with other stimuli based on the hearing ability of the user.

It is clear from the research presented that more BCI studies should incorporate more qualitative data collection. The insights provided by the users would not have been otherwise identified with EEG data alone.

Future work should investigate whether neurofeedback training for MRCP can improve symptoms in those with ASD. It should also be investigated whether other algorithms may improve MRCP detection in adults with ASD, either in detection accuracy or detection time. When detection is reliable enough to get sufficient detection accuracy, then it should be investigated if MRCP neurofeedback training can improve MNS activation, which could be measured via *mu* rhythm suppression.

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8. Appendix

Post-Section Questionnaire

Based on the interface you just used, please answer the following questions below:

	Very Unpleasant		Satisfactory/ Neutral		Very Pleasant
	|		|		|
	1	2	3	4	5
On the scale to your right, please indicate how you felt when interacting with that type of interface:	◯	◯	◯	◯	◯

Please tell us a little bit more about why you feel this way: (You do not need to fill in the whole space)

In your opinion, would you feel comfortable using this type of system to control a machine or computer?

◯ **YES** ◯ **NO**

Version 1.3, last revised on December 8th 2017.

FIGURE 9 The template of the survey presented to participants.

TABLE 13 Responses of question 2 from survey, which asked "Please tell us a little bit about why you felt this way". Note that minor spelling errors have been corrected in the table below, such as missing or extra letters to a word. Point form notes have been separated by commas. Dashes (-) indicate that nothing was written down.

Participant	Movement Type	Interface Type	Response
S02	Real	Auditory	"Voice of the computer is pleasant. However, the final call ('go') is not very 'enthusiastic.' I would expect it to be more encouraging/engaging."
		Visual	"The chair is a bit uncomfortable."
		Haptic	"This type of interface is very tactile. The best one of all three (in my opinion). Does not require visual nor audible attention."
	Imagined	Auditory	"The enthusiasm in voice commands decreases with time. 'Go' should be louder."
		Visual	"Requires lots of attention. Waiting for the stimuli induces fatigue"
		Haptic	"This type of experiment engages imagination. There is some learning curve to it. In order to use it well, definitely lots of practice is required."
S03	Real	Auditory	"A little bit annoying, 'someone' tells you what to do"
		Visual	"Annoying, you have to be very focused on the screen, you 'sleep' during this test"
		Haptic	"Doesn't make noise, little device"
	Imagined	Auditory	"Difficult to imagine your foot moving, need to train to do that well"
		Visual	"More difficult because you have to focus on the screen so you're less focused on your foot"
		Haptic	"Not disturbing, you can focus on your task"
S04	Real	Auditory	"Auditory triggers were easier to follow/stay focused on"

		Visual	“In between the haptic and auditory cues, easier to follow than haptic but less than auditory”
		Haptic	“Vibrations helped focus on the task”
	Imagined	Auditory	“Eyes are starting to fatigue”
		Visual	-
		Haptic	“Same comment as before”
S05	Real	Auditory	“Audio cue helped to focus on the cues more than visual/tactile. ‘Zoned out’ during experiments, focused less on sight and more on hearing/touch.”
		Visual	-
		Haptic	“Tactile sensation was more ‘compelling’ than usual. Felt a stranger urge to move my foot at the cue.”
	Imagined	Auditory	Felt more like I was trying not to move my foot, rather than imagining it moving.”
		Visual	“Somewhere between audio vs. haptic in terms of an urge to move. More concerned with timing than haptic.”
		Haptic	Less anticipation than audio cues. Felt more deliberate about moving my foot. Less of an urge to move
S08	Real	Auditory	“The sound wasn’t stressful, but it stressed me a bit for the timing.”
		Visual	“It had no pressure, I had the time to see it coming and move in consequence.”
		Haptic	-
	Imagined	Auditory	-
		Visual	“In the end, I really wanted to move my foot!”
		Haptic	“Tring to figure out how to move but not move in the end is hard.”
S09	Real	Auditory	“I was comfortable with this type of cue.”
		Visual	-
		Haptic	“I feel that the vibration was distracting and I had to focus at my wrist which made me uncomfortable. To be more specific, part of

			my brain was busy waiting for the command."
	Imagined	Auditory	"It was a good experience and could follow the instructions after 5 trials (could imagine the movement better)."
		Visual	"I was comfortable with this interface. I am the type of a person who learns things visually so this visual helped me be more focused on the task. And I think that can be a factor."
		Haptic	"I was surprisingly very comfortable with the haptic cue for imaginary movement."
S10	Real	Auditory	"Found voice was the hardest to stay focused/on task (though perhaps this is trial #3)."
		Visual	"More intrusive than vibration."
		Haptic	"Easy to feel, gentle, non-intrusive."
	Imagined	Auditory	"Getting quite tired/made me feel tired. Perhaps if the voice was different it would help with the engagement."
		Visual	"Much more difficult than real motion; harder to remain focused."
		Haptic	"Most engaging and not intrusive at the same time. I felt this was the easiest to interact with."
S11	Real	Auditory	-
		Visual	-
		Haptic	-
	Imagined	Auditory	-
		Visual	-
		Haptic	-
S14	Real	Auditory	"Good – voice kept my attention more, but the tone of voice was a little unenthusiastic!"
		Visual	"Easy to understand."
		Haptic	"Requires more thinking – need to keep track of pulses, whereas other methods show 3, 2, 1 differently."
	Imagined	Auditory	"Probably the best of the imagined ones. Voice guiding just seemed natural."

		Visual	-
		Haptic	“Even more thinking here.”
S15	Real	Auditory	“The women’s voice is a little terrifying. It feels like she is giving me order to obey.”
		Visual	“A little bit silent. I feel I can be easily distracted by the environment.”
		Haptic	“The vibration is weaker than my wristband. So it’s less annoying.”
	Imagined	Auditory	“It gives the accurate timing for moving my leg.”
		Visual	“Better timing than the audio cue.”
		Haptic	“Gives a better timing for moving my leg than the audio one.”
AS01	Real	Auditory	“I feel nothing wrong with anything and when the white cross appears, I tense myself in preparation.”
		Visual	“It was calming getting ready to do the action when a green square appeared.”
		Haptic	“Very relaxing.”
	Imagined	Auditory	“Feeling easier to do.”
		Visual	“Pretty hard to accurately calculate the mental kick but it’s easy to learn.”
		Haptic	“Calm but slightly difficult moving my foot.”
AS02	Real	Auditory	-
		Visual	-
		Haptic	“I like this method the best so far because, with the sound I might tune it out by accident, and with the shapes I might not pay attention. But with the vibrations, I’m forced to pay attention. (Vibrations on wrist) were the best so far”
	Imagined	Auditory	-
		Visual	“Watching the shapes made me feel tired and fight to keep my eyes open.”
		Haptic	-
AS03	Real	Auditory	-

		Visual	-
		Haptic	-
	Imagined	Auditory	-
		Visual	-
		Haptic	-
AS04	Real	Auditory	“Easiest one to follow.”
		Visual	“In some applications this may be good, little hard to keep looking sometimes.”
		Haptic	“Vibration felt a bit odd at first but I got used to it.”
	Imagined	Auditory	“Easiest to follow.”
		Visual	“Little hard to focus on that and think about moving.”
		Haptic	“Easiest to follow while thinking about moving.”
AS05	Real	Auditory	“As this is the third time around, my ankle is getting a little weaker and tired from all the moving so far, but generally comfortable and easy instructions to follow.”
		Visual	“I like rhythms. I find them calming. I was able to concentrate and focus because I knew when the green light was going to happen. (I had a red light countdown.) And there was only one instruction: to point my toes up. (Therefore it is less overwhelming.)”
		Haptic	“I don’t particularly like things that vibrate, but it wasn’t so unpleasant that I needed to stop. (Sensory processing disorder is part of ASD, and I’m very sensitive to sound and tactile things.) It also tends to itch in the area of buzzing if it goes on long enough. But generally comfortable.”
	Imagined	Auditory	“That was cool. I would like to know how easily one could see my imagination doing the thing. It’s so amazing to be able to control something using your brain. I tried different speeds and also imaging the muscles moving.”

		Visual	"This was so much easier. I found it really easy to imagine the muscles moving so it felt like I was actually moving them up and down, but it wasn't actually going anywhere. Less anxiety this time. I could change the speed more easily as well. (picture it just as clearly.)"
		Haptic	"This one was particularly itchy. I also got very sleepy. I started to have a. lot of anxiety as it was going and I wanted it to be over. I found it more difficult to concentrate."
AS06	Real	Auditory	"Instruction on desired movement a little but overall went well."
		Visual	"I have a little delay in processing visual cues sometimes."
		Haptic	"I prefer vibration alerts."
	Imagined	Auditory	"Imagined response is challenging."
		Visual	"Nothing 'special' but needed the practice round to get visualizing 'down.'"
		Haptic	"Imagined movement isn't easy have lower 'score.'"
AS07	Real	Auditory	-
		Visual	"Some difficulty with lifting foot only for an instant."
		Haptic	"This felt easily like a very mild shock collar."
	Imagined	Auditory	"Lack of focus this instance."
		Visual	-
		Haptic	"Unsure how to precisely perform test. Still a shock collar, though."
AS08	Real	Auditory	-
		Visual	"Strange."
		Haptic	-
	Imagined	Auditory	-
		Visual	-
		Haptic	-
AS09	Real	Auditory	"The test was very simple and direct, only it was a bit harder to know how long

			to keep my foot raised before the next sequence."
		Visual	"The test was very simple and direct."
		Haptic	"The test was very simple, and very direct."
	Imagined	Auditory	"This was slightly easier than the previous test as I was able to concentrate better by closing my eyes to envision my foot raising as needed. This test still required some concentration."
		Visual	"This was harder than the previous three which involved actual movement, but I found it easier than imagined."
		Haptic	"This skill required some concentration but was easier than the other imaginary test as I was able to time the envisioning of lifting my foot with the timed feel of the buzz from the bracelet."
AS10	Real	Auditory	"With voice, you can benefit it with the muscle reaction, with the tone, the pronunciation and the rhythm."
		Visual	"It feels like that it can be used for other things, it felt like nothing for me."
		Haptic	"It's a new way of using your body, like you are of that of a baby, it's getting used gradually from time to time that it will become a part of you like a prosthetic for example."
	Imagined	Auditory	"I feel like it benefits a lot from thinking what you want to do in your head and get a reaction out of it."
		Visual	"I feel like thinking what you're going to do adds to the system on making it more precise for the general public."
		Haptic	"It gives reactions to that of objectives, such as waking up at a certain time for example."

TABLE 14 The MRCP features collected for each participant and interface, averaged across 20 trials.

Participant	Group	Movement Type	Cue Type	NS1 (μV/s)	NS2 (μV/s)	PA (μV)	RR (μV/s)
AS01	ASD	Real	Auditory	-0.8366	-4.2873	-4.2934	4.4973
AS01	ASD	Real	Visual	-3.5230	-5.7513	-6.7411	4.7781
AS01	ASD	Real	Haptic	-3.8554	-3.2700	-5.0238	2.4880
AS01	ASD	Imagined	Auditory	1.1443	-1.9979	0.0130	0.6895
AS01	ASD	Imagined	Visual	-0.9559	-1.5888	-1.6759	0.9228
AS01	ASD	Imagined	Haptic	0.5368	-3.8027	-0.9154	0.4581
AS02	ASD	Real	Auditory	-1.9713	-4.2650	-4.7455	4.2836
AS02	ASD	Real	Visual	0.2720	-5.0386	-4.6152	5.0857
AS02	ASD	Real	Haptic	-1.1788	-4.3096	-3.9322	2.8836
AS02	ASD	Imagined	Auditory	-1.4267	-0.8025	-1.3439	0.2711
AS02	ASD	Imagined	Visual	1.1522	-3.3516	-1.4189	0.6499
AS02	ASD	Imagined	Haptic	-1.5807	-1.9658	-2.0858	2.2775
AS03	ASD	Real	Auditory	1.7172	-3.8433	-2.0201	4.3901
AS03	ASD	Real	Visual	5.9577	2.6133	1.2539	1.0083
AS03	ASD	Real	Haptic	1.3184	-4.0083	-1.6720	3.1997
AS03	ASD	Imagined	Auditory	-3.1787	-5.1002	3.1997	-0.1992
AS03	ASD	Imagined	Visual	-3.4027	-3.7831	-2.1102	0.0842
AS03	ASD	Imagined	Haptic	-7.1097	-3.8768	-5.7232	1.9659
AS04	ASD	Real	Visual	-8.4696	-13.6568	-17.9172	15.9779

AS04	ASD	Real	Auditory	-3.9253	-17.4085	-14.3433	13.8567
AS04	ASD	Real	Haptic	-4.8132	-11.9225	-13.8908	15.8052
AS04	ASD	Imagined	Visual	1.2935	-8.7270	-3.2504	5.2760
AS04	ASD	Imagined	Auditory	-1.3290	-1.7331	-4.1925	2.3183
AS04	ASD	Imagined	Haptic	-5.9395	-12.4434	-12.3487	6.8082
AS05	ASD	Real	Visual	-5.7393	-2.2980	-5.8694	4.7836
AS05	ASD	Real	Auditory	-0.7565	-3.1023	-3.4155	3.5858
AS05	ASD	Real	Haptic	0.5816	-2.8149	-1.6315	2.9641
AS05	ASD	Imagined	Visual	-1.4151	-2.8385	-1.9927	0.4914
AS05	ASD	Imagined	Auditory	-2.9906	-0.6077	-1.8283	1.3266
AS05	ASD	Imagined	Haptic	-1.9202	-3.1509	-3.2676	1.4301
AS06	ASD	Real	Visual	-0.0340	-6.2115	-5.7911	4.5573
AS06	ASD	Real	Auditory	-0.7888	-4.7558	-4.2616	3.6070
AS06	ASD	Real	Haptic	-0.9863	-12.7672	-7.9628	5.3156
AS06	ASD	Imagined	Visual	-0.3967	-6.8322	-3.2531	2.2951
AS06	ASD	Imagined	Auditory	-0.8831	-2.1166	-1.3797	2.1652
AS06	ASD	Imagined	Haptic	-0.1720	-5.2595	-3.0209	2.1138
AS07	ASD	Real	Visual	-10.0147	-16.3641	-16.7763	10.8364
AS07	ASD	Real	Auditory	-9.9453	-22.1835	-18.5721	12.0033
AS07	ASD	Real	Haptic	-9.2255	-12.2556	-15.5175	6.6166
AS07	ASD	Imagined	Haptic	-9.0657	-12.3708	-15.4327	11.7817
AS07	ASD	Imagined	Visual	-11.4181	-5.9609	-13.6089	9.0479
AS07	ASD	Imagined	Auditory	-5.9669	-8.7964	-12.4918	12.4238

AS08	ASD	Real	Auditory	-2.6700	-11.5656	-8.9711	5.0609
AS08	ASD	Real	Visual	-6.6418	-11.1498	-12.4343	8.2123
AS08	ASD	Real	Haptic	-2.1580	-8.3739	-6.6342	4.6813
AS08	ASD	Imagined	Haptic	0.3078	-0.9312	-1.4494	1.6852
AS08	ASD	Imagined	Visual	-0.6289	-4.3118	-1.1939	-0.3687
AS08	ASD	Imagined	Auditory	-0.1702	-2.4296	-1.3670	1.6648
AS09	ASD	Real	Auditory	-2.3669	-5.8913	-5.8913	7.1594
AS09	ASD	Real	Visual	-9.7675	-7.8123	-12.1806	6.9908
AS09	ASD	Real	Haptic	-7.5168	-14.0058	-14.4451	9.3815
AS09	ASD	Imagined	Haptic	-5.7947	-0.9908	-4.8774	1.2483
AS09	ASD	Imagined	Visual	-2.7939	-3.0885	-1.7912	0.0736
AS09	ASD	Imagined	Auditory	-4.6733	-0.7202	-0.3700	-2.0526
AS10	ASD	Real	Auditory	-5.0577	-0.5277	-4.2978	1.5379
AS10	ASD	Real	Visual	-1.6335	-3.3913	-2.9920	-0.1565
AS10	ASD	Real	Haptic	-2.5451	-3.2199	-2.7039	1.6769
AS10	ASD	Imagined	Haptic	0.9980	-2.5263	-0.5385	-0.0052
AS10	ASD	Imagined	Visual	-2.3960	-2.3188	-3.6331	1.7594
AS10	ASD	Imagined	Auditory	-4.0180	-3.3338	-1.7864	0.4438
S02	Neurotypical	Real	Visual	-5.2507	-10.1998	-10.5044	8.4846
S02	Neurotypical	Real	Haptic	-6.4515	-6.5739	-10.7751	9.0740
S02	Neurotypical	Real	Auditory	-3.9218	-6.4390	-10.6477	9.0096
S02	Neurotypical	Imagined	Visual	-0.6445	-4.8102	-3.3709	2.5489
S02	Neurotypical	Imagined	Haptic	0.9012	-3.3185	-2.1963	1.3851

S02	Neurotypical	Imagined	Auditory	-3.6800	-2.7245	-5.8940	5.2208
S03	Neurotypical	Real	Auditory	-5.3869	-12.7539	-13.1747	9.3049
S03	Neurotypical	Real	Visual	-16.9581	-21.3018	-18.3568	5.5037
S03	Neurotypical	Real	Haptic	-15.8096	-12.3031	-18.9176	10.0950
S03	Neurotypical	Imagined	Auditory	-8.4580	-6.7134	-7.0709	2.5229
S03	Neurotypical	Imagined	Visual	-16.2918	-17.1919	-15.8261	3.1023
S03	Neurotypical	Imagined	Haptic	4.7644	-4.4755	0.6024	0.6667
S04	Neurotypical	Real	Auditory	-4.4158	-9.3018	-7.9687	4.1707
S04	Neurotypical	Real	Visual	-6.4341	-10.1457	-10.3461	5.5619
S04	Neurotypical	Real	Haptic	-9.3824	-8.5822	-11.6975	6.1466
S04	Neurotypical	Imagined	Auditory	-5.0494	-6.6620	-6.0393	4.0025
S04	Neurotypical	Imagined	Visual	-2.9678	-8.5883	-5.3462	4.7859
S04	Neurotypical	Imagined	Haptic	-3.1384	-5.4772	-4.7995	3.2205
S05	Neurotypical	Real	Auditory	-18.3827	-16.5494	-17.8757	6.7094
S05	Neurotypical	Real	Visual	-16.6178	-14.5323	-13.6463	6.5642
S05	Neurotypical	Imagined	Auditory	-12.1274	-2.8153	-10.9040	7.6279
S05	Neurotypical	Imagined	Visual	-10.8708	-13.1942	-10.9583	8.4581
S05	Neurotypical	Imagined	Haptic	-9.7743	-9.4155	-10.9583	8.4194
S08	Neurotypical	Real	Visual	-13.4019	-6.0967	-6.0967	10.7324
S08	Neurotypical	Real	Auditory	-10.7357	-6.0791	-12.5947	7.9762
S08	Neurotypical	Real	Haptic	-14.0403	-6.6064	-16.0121	9.5008
S08	Neurotypical	Imagined	Visual	-7.2273	-4.1906	-5.4726	2.0173
S08	Neurotypical	Imagined	Auditory	-8.9075	-4.8908	-10.8359	6.0788

S08	Neurotypical	Imagined	Haptic	-4.3475	-2.0660	-6.7237	6.0143
S09	Neurotypical	Real	Haptic	-13.6889	-12.4655	-19.4868	15.9445
S09	Neurotypical	Real	Visual	-9.3711	-10.6046	-15.9635	14.6782
S09	Neurotypical	Real	Auditory	-10.9719	-12.4589	-18.0024	15.5910
S09	Neurotypical	Imagined	Haptic	-2.8565	-4.6599	-7.9625	6.9437
S09	Neurotypical	Imagined	Visual	-6.2371	-5.2812	-8.7225	6.4788
S09	Neurotypical	Imagined	Auditory	-6.0281	-3.5665	-7.5247	5.9898
S10	Neurotypical	Real	Haptic	-12.8327	-11.1417	-16.2326	10.5268
S10	Neurotypical	Real	Visual	-7.7776	-12.3591	-11.0291	9.5752
S10	Neurotypical	Real	Auditory	-7.1260	-14.2581	-13.7451	8.8347
S10	Neurotypical	Imagined	Haptic	-5.9731	-4.3750	-6.9685	4.4416
S10	Neurotypical	Imagined	Visual	-1.8303	-8.4418	-5.2464	3.7672
S10	Neurotypical	Imagined	Auditory	-5.4715	-3.3135	-4.9440	1.3804
S11	Neurotypical	Real	Haptic	-6.4190	-4.4948	-9.4287	9.5050
S11	Neurotypical	Real	Visual	-4.8922	-6.4560	-8.2242	7.3183
S11	Neurotypical	Real	Auditory	-5.5653	-2.2719	-8.5292	8.8488
S11	Neurotypical	Imagined	Haptic	-8.7982	-1.8715	-9.5121	6.4496
S11	Neurotypical	Imagined	Visual	-10.4043	-4.9792	-10.6327	5.4681
S11	Neurotypical	Imagined	Auditory	-2.8408	-4.5848	-4.3319	3.4948
S14	Neurotypical	Real	Haptic	-0.9156	-3.5294	-3.2289	3.1347
S14	Neurotypical	Real	Visual	-3.9785	-4.4822	-4.4822	3.4465
S14	Neurotypical	Real	Auditory	1.4167	-6.8763	-2.3369	2.5925
S14	Neurotypical	Imagined	Haptic	-0.3512	-2.8846	-2.6729	4.1537

S14	Neurotypical	Imagined	Visual	-7.9240	-2.7124	-6.0241	2.0686
S14	Neurotypical	Imagined	Auditory	-5.7677	-1.9608	-6.0922	8.1997
S15	Neurotypical	Real	Visual	-2.7637	-8.9956	-5.6370	3.2990
S15	Neurotypical	Real	Auditory	0.0210	-2.7088	-4.3808	5.4401
S15	Neurotypical	Imagined	Haptic	-10.5618	-5.5770	-10.3422	8.1559
S15	Neurotypical	Imagined	Visual	-6.9786	-4.5751	-8.5133	4.1527
S15	Neurotypical	Imagined	Auditory	-7.9693	-4.1271	-8.0264	4.9562