**A Feasibility Study: Using Brain Computer Interface For Communication In Non-Speaking Autistic (NSA) Population**

**[3-page 0.5 inch margins]**

**Background**

*Non-speaking autistic population*

The main specifier for autism diagnosis is language problems (*Diagnostic and Statistical Manual of Mental Disorders*, 2013). Around 25% to 35% of autistic population are not able to speak (Baghdadli et al., 2018; Rose et al., 2016; Wodka et al., 2013), however “Non-Speaking doesn't mean Non-Thinking,” as it mentioned in a poem by a non-speaking child (Grodin & McDonough, 2021). Autistic population should be supported to communicate their desires, thoughts and feelings. However, there is few studies for teaching verbal communication to non-speaking autistic population based on a recent review (Koegel et al., 2020). Autistic people need a sense of belonging to society and social inclusion, but feeling isolated could affect their mental health and trigger a variety of emotional problems such as suicidal ideas (Mitchell et al., 2021) and self-injury behaviors, especially in non-speaking autistic population (Richards et al., 2012).

*Disadvantage of current AAC*

Augmented and Alternative Communication (AAC) is a substitute option for non-speaking autistic population to communicate. A meta-analysis by comparing different types of AAC applications (e.g., Picture Exchange (PE), Picture Exchange Communication Systems (PECS), Speech Generating Devices (SGD)), reported that autistic population prefer using technology-based AAC for speaking and communicating (Aydin & Diken, 2020). However, current AAC devices for non-speaking autistic population are not always equitably accessible in terms of learnability, availability, affordability (Baxter et al., 2012; Elsahar et al., 2019; Moorcroft et al., 2019). The use of AAC devices needs training for autistic individuals and extensive theoretical and practical experiences for teachers (Baxter et al., 2012; Moorcroft et al., 2019). Further, motor skills problems in autistic population can limit the use of some AAC application, such as manual sign apps (Aydin & Diken, 2020).

*BCI and its application*

There have been growing interests in using brain-interface technology (BCI) based on electroencephalogram (EEG) for a variety of conditions such as autism, ageing, physical disabilities (Hossain & Doulah, 2020). The classic applications of using BCI is to detect the pattern of task imagery. Researchers report that motor imagery signals can be detected using EEG signals to help people with disabilities including autism, physical disabilities, ageing adults (Hossain & Doulah, 2020) and a variety of outcomes, including rehabilitation (e.g., therapies to regain physical abilities), diagnosis (e.g., autism, coma), recreation (e.g., gaming, art), assistive technology (e.g., communication, mobility) (Zander et al., 2010). BCI is easy to use and does not need training or using motor skills (Elsahar et al., 2019). Researchers state that EEG-based BCI with an accurate algorithm using machine learning (ML) could be influential in leading us to understand autism better (M. G. Ezabadi & M. H. Moradi, 2021).

*BCI application in autism*

Based on our brief literature review (from 2015 to 2022), BCI studies in autism field can be classified in two main class, i.e., identification and rehabilitation purposes. For example, BCI can identify sound/music preferences (Cibrian et al., 2018) and the music aligned with autistic child’s mood for using in therapy (Niu et al., 2022), mental stress during arithmetic tasks (Sundaresan A et al., 2021), anxiety state (Penchina et al., 2020), emotional state (distress vs non-distress), engagement level in task, and mental workload (Eldeeb et al., 2021; Fan et al., 2018; Val-Calvo et al., 2017), interest to tasks by monitoring the level of attention of autistic children (Ravindranathan et al., 2020), and social joint attention of autistic children (de Arancibia et al., 2020; M. G. Ezabadi & M. H. Moradi, 2021; Simoes et al., 2020). Rehabilitation-purposed BCIs for autism improves: attention using a BCI-based video game (Mercado et al., 2021), social skills using neurofeedback training (Teo et al., 2021), social joint attention (Amaral et al., 2017; Bittencourt-Villalpando & Maurits, 2020; Castelo-Branco, 2019), learning to interpret emotional facial expressions and social skills (White et al., 2016) and learning driving to autistic adolescents (Fan et al., 2018).

Current studies indicate that using BCI can be useful and feasible in autism population to improve social skills and teach some tasks. However there is no evidence on using BCI in verbal communication for autism, consistent with the result of a recent review (Williams & Gilbert, 2020). There are a variety of BCI studies on verbal communication and AAC devices in other population (Elsahar et al., 2019; J. van Kokswijk & M. Van Hulle, 2010; Khachatryan et al., 2015, 2016, 2018; Mora-Cortes et al., 2014; Wittevrongel et al., 2018) that could be enlightening for our journey by applying their principles for autism population. *Our aim is to use an EEG-based BCI for Non-Speaking Autism population to communicate.*

**Aim**

We aim to detect brain signal patterns using an EEG-based BCI in response to audio-visual stimuli in NSA population. Further, we aim to translate the recognized brain signal patterns from autistic participants into audio speech presented in a phone app or computer.

**Method**

*Participants*. We will recruit participants (N= 15 , age = ) from autism communities and organizations. They may speak minimally or not be able to speak. For minimally speaking participants, word counts will be assessed based on the guideline to define the level of speech (Koegel et al., 2020). Inclusion criteria: participants should have a formal diagnosis either autism or unspecified neurodevelopmental disability. Those with mild intellectual disabilities (ID) and without ID will be included. Exclusion criteria: participants who do not have the mentioned formal diagnoses, those with epilepsy history, those who have metallic cranial implants and those with moderate or and most significant intellectual disabilities will be excluded.

*Study Protocol*. There are difficulties in training BCI for Autistic individuals (Kashihara, 2014). However, to control errors, there are a variety of approaches. For instance, a hybrid BCI that is a combination of Event Related Desynchronization (ERD)-based active BCI with eye tracking, will be applied. And then, a passive BCI based on human error processing, bringing new forms of automated adaptation in BCI (Zander et al., 2010). Further, using multimodal components (e.g., audio-visual) improves the accuracy in using BCI for speech compared to use one modal (Brumberg et al., 2018).

Participants will receive multimodal audio-visual stimulus simultaneously including a 2-dimentioanl picture and a rhythmic audio playing the name of the picture. The preferences of autistic population in terms of pictorial and musical/rhythmic features are considered. Further, rhythmic-auditory stimuli can benefit the research participants and outcome via multiple perspective. First, interesting stimuli for participants can improve the accuracy of signal pattern detection as they are more likely to be willing to pay attention to their favorite stimuli (Shamsi et al., 2020). Also, in language processing features, evidence recently emphasize the component of rhythm in language. For instance, rhythmic feature in communication underlies inference, generation and prediction of morphemes, words and phrases without prior knowledge (Meyer et al., 2020). Further, “Rhythmic auditory cueing” is applied for rehabilitation practices (Hardy & LaGasse, 2013), based on “neurologic music therapy’s" (Thaut, 2007) rational that uses rhythmic activities to improve cognitive, sensory and motor functions (Fedotchev, Dvoryaninova, et al., 2019; Fedotchev et al., 2016; Fedotchev, Parin, et al., 2019; Hardy & LaGasse, 2013; Mayer-Benarous et al., 2021). Last but not least, BCI studies indicate that rhythmic elements in stimuli can improve the accuracy of the signal classification and decrease fatigue among participants (Shamsi et al., 2020).

The procedure is identical for all participants. The first phase is to train data through presenting audio-visual stimuli simultaneously to each participant. Overall, there are 4 runs of trials. Each run has 10 stimuli. Each audio-visual stimuli will be repeated 30 times, presented 30 seconds, in random, with a random 3-5 seconds resting time. Participants will be trained to look at the picture and listen to the audio played with each picture…

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//?//Speech entails multiple rhythms: intonation (-4 Hz), syllables (4-8 Hz) and phonemes (>30 Hz) (Watanabe, 2019). Synchronization phenomenon between rhythm in speech and neural oscillations in delta, theta and gamma frequency band and neural source of this synchronization will be measured. Neural phase synchronization can distinguish words using EEG-based classification (Watanabe, 2019).

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*EEG acquisition*. A 32-channel portable EEG-based BCI will record brain signals.

*SSVEP Paradigm*. Studies indicate that this paradigm can be applied for a variety of population, it does not need an overt response and can be conducted in a short period of time (Dickinson et al., 2018).

SSVEP will be evaluated based on ITR, assessed in bits per minute and the accuracy of classification (Mahmood et al., 2019; Obermaier et al., 2001):

*BCI-P300 Paradigm*

“The stimulus presentation paradigm with the BCI-P300 is in many ways suitable for studies where the detection of EEG reaction characteristics for particular classes of stimuli and the predictive capacity of the EEG in terms of assigning one or another stimulus to particular classes are important.” (Ganin et al., 2018).

*Measures*

Vineland Adaptive Behavior Scales (VABS)-Third edition (Cicchetti et al., 2013; Sparrow, 2011). This standardized semi-structured interview measures personal and social skills, receptive and expressive communication utterance and motor skills for all ages.

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**Data analytic plan**

Recently, Deep Neural Networks (DNNs) for BCI data classification was adapted for language modelling (Kostas et al., 2021) to generate automatic speech recognition(Kostas et al., 2021), using a wav2vec 2.0 framework (Baevski et al., 2020), for a self-supervised speech recognition through “encoding speech audio via a multi-layer convolutional neural network and then masking spans of the resulting latent speech representations, these then can be fed to a transformer network to build representations capturing information from the entire sequence” (Kostas et al., 2021). We will use this approach to recognize brain signal patterns in reacting to audio-visual stimuli.

*Performance analysis*.

*EEG analysis*.

*Preprocessing*.

*BCI Decoder*.

The algorithm will be detected and classified using Deep Neural Networks (DNNs) techniques.

*Performance Analysis*.

Other requirements for application

*Which MIDB cores will be utilized to facilitate the research? (½ page)*

Considering the interdisciplinary nature of proposed project, we will collaborate across multiple departments/centers at MIDB as follows. Jessica Simacek, with extensive knowledge in autism and interdisciplinary research areas, the director of “*TeleOutreach Core (TOC)*” core and Jed Elison, with extensive experiences in interdisciplinary area in brain imaging and autism, the director of “*The Measurement and Human Phenotyping Core (MHPC)*” contribute to this project. TOC and MHPC will facilitate this project by providing the related knowledge and skills on autism, brain science as well as equipment (e.g., EEG), data acquisition (EEG data) and testing rooms (to conduct survey and experiments).

***Roles?*** … the ***CNDB clinical research center*** ?

*Applications should provide a statement of how the work fits the mission of the MIDB (½ page) and confirm whether the study will take place at MIDB.*

*Updated CV*

*Letter of endorsement from proposed mentor(s)-1 page.*

*Detailed budget and budget justification with timeline*

*Please include information regarding the project’s IRB/IACUC status.*

The IRB application for the proposed project will be started once the proposal will be granted.

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*[to explain multi-department team]*

The use of BCI, which requires an interdisciplinary cooperation of researchers (with expertise in rehabilitation science, psychologist, clinicians, engineering, machine learning, signal processing) to improve its applicability and convenience as well as benefits for clients (Niu et al., 2022).