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

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**Background**

*Non-speaking autistic population*

The main specifier for autism diagnosis is language problems 1. Around 25% to 35% of autistic population are not able to speak 2–4, however “Non-Speaking doesn't mean Non-Thinking,” poem by a non-speaking poet 5. 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 6. 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 7 and self-injury behaviors, especially in non-speaking autistic population 8.

*Disadvantage of current AAC*

Augmented and Alternative Communication (AAC) is another option for non-speaking 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 9. However, current AAC devices for non-speaking autistic population are not always equitably accessible in terms of learnability, availability, affordability 10–12. The use of AAC devices needs training for autistic individuals and extensive theoretical and practical experiences for teachers 10,12. Further, motor skills problems in autistic population can limit the use of some AAC application, such as manual sign apps 9.

*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 13. 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 13 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) 14.

*Benefit of BCI*

BCI is easy to use and does not need training or using motor skills 11. Researchers state that EEG-based BCI with an accurate algorithm using machine learning (ML) could be influential in leading us to understand autism better 15.

*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 16 and the music aligned with autistic child’s mood for using in therapy 17, mental stress during arithmetic tasks 18, anxiety state 19, emotional state (distress vs non-distress), engagement level in task, and mental workload 20–22, interest to tasks by monitoring the level of attention of autistic children 23, and social joint attention of autistic children 15,24,25. Rehabilitation-purposed BCIs for autism improves: attention using a BCI-based video game 26, social skills using neurofeedback training 27, social joint attention 28–30, learning to interpret emotional facial expressions and social skills 31 and learning driving to autistic adolescents 21.

Current studies indicate that using BCI can be useful and feasible in autism population though we did not find any study working on verbal communication for autism, consistent with the result of a recent review 32. However, there are a variety of BCI studies on verbal communication and AAC devices in other population 11,33–38 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

We aim to translate the recognized brain signal patterns from autistic participants into audio speech presented in a phone app or computer screen

**Method**

*Participants*. We will recruit participants (N= , age = ) from autism communities and organizations. They may speak minimally or not be able to speak. For minimally speaking participants, word counts will be reported based on the guideline in a systematic review paper 6.

*Study Protocol*. Participants receive multimodal audio-visual stimulus simultaneously including a picture and playing the name of the picture via a rhythmic-expressed/articulated/pronounced audio. The preferences of autistic population in terms of pictorial and musical/rhythmic features are considered. Adding rhythmic-auditory aspect to visual stimuli can benefit the research outcome via multiple perspective. First, interesting stimuli for participants can improve the accuracy39. Also, in language processing features, evidence recently emphasize the component of rhythm in language and state rhythmic feature in communication underlies inference, generation and prediction of morphemes, words and phrases without prior knowledge 40. Further, the studies report “Rhythmic auditory cueing” can be effective for rehabilitation practices 41, referring to neurologic music therapy 42 that uses rhythmic activities to improve cognitive, sensory and motor functions 41,43–46. 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 39.

Speech entails multiple rhythms: intonation (-4 Hz), syllables (4-8 Hz) and phonemes (>30 Hz) 47. 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 47.

*Stimulus Feedback*.

*EEG acquisition*. We will use a mobile/portable EEG-based BCI to extract brain signals of non-speaking autistic participants when they are looking at pictures and hearing the name of the picture (multimodal approach). Then, the algorithm will be classified using ML techniques.

There are difficulties in training BCI for Autistic individuals 48. However, to control errors, there are a variety of approaches. For instance, a combination of Event Related Desynchronization (ERD)-based active BCI with gaze control, a hybrid BCI, may resolve the midas touch problem. And then, a passive BCI based on human error processing, bringing new forms of automated adaptation in BCI 14. Further, using multimodal components (e.g., audio-visual) improves the accuracy in using BCI for speech compared to use one modal 49.

*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.” 50.

*Measures*

Vineland Adaptive Behavior Scales (VABS)-Third edition 51,52. This standardized semi-structured interview measures personal and social skills, receptive and expressive communication utterance and motor skills for all ages.

**Data analytic plan**

We use Deep Neural Networks (DNNs) for BCI data classification was adapted for language modelling 53 to generate automatic speech recognition. A study 53 refers to a wav2vec 2.0 framework 54, used 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” 53.

*Performance analysis*.

*EEG analysis*.

*Offline and online preprocessing*.

*BCI Decoder*.

*Performance Analysis*.

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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 17.