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

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**Background**

*Non-speaking autistic population*

Language is main tool to socialize and express our thoughts while this may not be similar in autistic population as language problem is main specifier for autism diagnosis 1. Even around 25% to 35% of autistic population are not able to speak 2–4.

“Non-speaking doesn't mean non-thinking,” mentioned by a non-speaking poet 5. Autistic population should be supported to communicate their desires, thoughts and feelings. They also need a sense of belonging to society and social inclusion, but feeling isolated could affect their mental health and trigger suicidal ideas 6 and a higher rate of self-injury behaviors in non-speaking autistic population 7.however, a recent review reports that there is few studies for teaching verbal communication to non-speaking autistic population 8.

*Disadvantage of current AAC*

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 for speaking and communicating 9. However, current AAC for non-speaking autistic population are not always equitably accessible in term of learnability, availability, affordability 10–12 and also need training in 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*

EEG based BCI can help interventional and diagnostic possibilities… BCI is easy to use and does not need physical or verbal respond…

*BCI application in autism*

BCI for autism population has been used to detect sound/music preferences for autistic children 15 and the music aligned with autistic child’s mood for using in therapy 16, to explore mental stress during arithmetic tasks 17, anxiety state 18, emotional state (distress vs non-distress), engagement level in task, mental workload 19–21, interest to tasks in autistic children by monitoring the level of attention 22, to classify joint attention 23–25, neurofeedback training to improve social skills 26, through a BCI video game to improve attention 27, and to teach driving to autistic adolescents 20, improve joint social attention 28–30 and to teach interpreting emotional facial expressions and social skills 31. Overall, EEG-based BCI with an accurate algorithm using machine learning (ML) could be influential in leading us to understand and help autism 24. There is a variety of signal sources for using AAC including touch/breath activated, imaging, mechanical methods, and BCI methods for non-autistic population 11, however there is no evidence of using BCI for speech in NSAP or generally, to AAC devices for autism.

**Aim**

BCI can benefit autistic population including NSAP by facilitating communication between their internal world and external world, their peers, family members, friends, non-autistic population and via social media. It does not need training or using motor skills 11. Based on our literature review exploring autism and BCI keywords in multiple databases, we did not find any study working on verbal communication in NSAP. Only a recent review refers to the point of lack of BCI study for assisting speech in NSAP 32, however, there are studies have explored verbal communication in other population 33–38 that could be enlightening for our journey by applying the principles for autism population. Therefore, our aim is to use BCI for NSAP to translate their brain signals to words and pictures, displayed on phone/computer monitor.

*Need for further research*

The use of BCI, which requires a 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 16,

**Method**

*Participants*. We will recruit participants (N= , age = ) from autism communities and organizations. They should not be able to speak or speak minimally. For minimally speaking participants, word counts will be reported based on the guideline in a systematic review paper 8.

*Study Protocol*.

*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 39. 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 40.

*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.” 41.

*Measures*

Vineland Adaptive Behavior Scales (VABS)-Third edition 42,43. 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 44 to generate automatic speech recognition. A study 44 refers to a wav2vec 2.0 framework, used for a self-supervised speech recognition 45.

*Performance analysis*.

*EEG analysis*.

*Offline and online preprocessing*.

*BCI Decoder*.

*Performance Analysis*.

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