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ENHANCED ANALYSIS OF EEG SIGNALS IN ASD INDIVIDUALS ACROSS EMOTIONAL STATES USING A WIRELESS DRY ELECTRODE EEG SYSTEM

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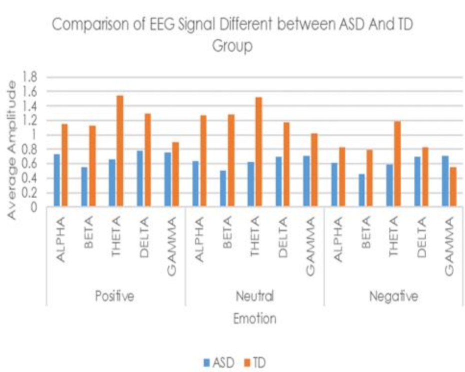
Graphical abstract



Abstract

Individuals with autism frequently struggle with emotion expression and emotion regulation. This study examines the relationship between electroencephalogram (EEG) band signal amplitude and mood in individuals with autism spectrum disorder (ASD) and typically developing (TD) individuals. Ten individuals with ASD and ten individuals with TD participated in this study. The participants wore wireless dry EEG sensors (MUSE 2) in order to get the EEG signal. The previously processed signals were classified as delta, beta, theta, delta, and gamma waves. In addition, positive mood, neutral emotion, and negative emotion are categorized in this study. In conclusion, the results of this investigation revealed substantial disparities in EEG signal amplitude between those with ASD and those with TD when experiencing distinct emotions. There are significant differences in 13 out of 20 EEG band signals from 4 electrodes for particular emotions in the ASD group.

Keywords: EEG, ASD, Emotion, T-test, Typical Development

Abstrak

Individu yang mempunyai autisme sering bergelut dengan ekspresi emosi dan peraturan emosi. Kajian ini mengkaji hubungan antara amplitud isyarat jalur electroencephalogram (EEG) dan mood dalam individu yang mengalami gangguan spektrum autisme (ASD) dan individu yang biasanya berkembang (TD). Sepuluh individu dengan ASD dan sepuluh individu dengan TD mengambil bahagian dalam kajian ini. Para peserta memakai penderia EEG kering tanpa wayar (MUSE 2) untuk mendapatkan isyarat EEG. Isyarat yang diproses sebelum ini dikelaskan sebagai gelombang delta, beta, theta, delta dan gamma. Mood positif, emosi neutral, dan emosi negatif dikategorikan dalam kajian ini. Kesimpulannya, keputusan penyiasatan ini mendedahkan perbezaan yang besar dalam amplitud isyarat EEG antara mereka yang mempunyai ASD dan mereka yang mempunyai TD apabila mengalami emosi yang berbeza. Terdapat perbezaan yang ketara dalam 13 daripada 20 isyarat jalur EEG daripada 4 elektrod untuk emosi yang berbeza dalam kumpulan ASD.

Kata kunci: EEG, ASD, Emosi, T-test, Perkembangan Biasa

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1.0 INTRODUCTION

Autism spectrum disorder (ASD) is a neurological and developmental disorder characterized by restricted or repetitive activities and behaviors, persistent weaknesses in communication, and social integration [1]. Asperger syndrome, pervasive developmental disorder, childhood disintegrative disorder, and autistic disorder are the subtypes of ASD [2].

There are mainly three levels of autism which are requiring support (level 1), requiring substantial support (level 2), and requiring very significant support (level 3). For level 1, the autistic patient will face difficulty in social interaction, and level 2 will have frequent restricted or repetitive behaviors and social interaction limited to a narrow exciting topic. For level 3, autism patients will have great distress and severe deficits in non-verbal or verbal social interaction skills [3]. Typically, autism patients of levels 1 and 2 will be selected for academic research because level 3 autism patients are difficult to communicate with and will not follow the researcher's instructions [4-6].

Repetitive behaviors, limited range of interest, communication impairment, and social interaction, such as reduced facial expression, body gestures, and eye contact, are the three core characteristics of autism spectrum disorder [7]. In addition, although autistic children tend to express their emotions similarly to typically developing children, they find it hard to describe them and always make other people misunderstand them during school.

Furthermore, some research indicates that children with autism have difficulty encoding gaze, face, or facial movements and cannot mimic body movements or actions [8, 9]. In addition, social interaction is closely related to emotional processing [10], and changing the emotional recognition mechanism in ASD may lead to social difficulties [11]. Most autistic children have difficulty processing emotional and sensory hypersensitivity [12]. A broader emotional focus may promote the generalization or translation of the therapy by more closely matching the manifestations of comorbid symptoms to improve the effectiveness of treatment [13].

Currently, there are several methods to classify human emotion, such as facial emotion recognition [14], electrodermal activity [15], speech recognition [16], EEG [17], and multi-model emotion recognition systems [18, 19]. In this study, portable EEG is selected as the instrument to collect autism group and typically developing group brainwaves because portable EEG is immune to surrounding factors such as temperature, lighting, body position, and sound noise. Thereby ASD therapists can obtain the best therapy performance by using Electroencephalogram (EEG) biofeedback.

ASD is a multifactorial neurodevelopmental disease caused by non-genetic or genetic factors. As early as the first three years of life, non-verbal communication and insufficient social interaction are considered ASD [20]. Delayed speech, social withdrawal, poor eye contact, and difficulty expressing, controlling, or understanding emotions are signs of ASD [21]. Electroencephalogram (EEG) neurofeedback is an effective solution to rectify the psychophysiological characteristics of autistic patients [22], and this makes ASD therapy very attractive due to these non-invasive effectual interventions [23]. Emotions and behaviors are the roots of all our thoughts and the basis for communication between brain neurons. Brain waves are generated by synchronized electrical impulses from many neurons that communicate with each other.

Electroencephalography (EEG) is one of the popular emotion classification methods because the accuracy of EEG is high. Still, it's sensitive to noise, and the setup process is time-consuming. The total recording electrode is 21 electrodes, and all the electrodes need to contact the head skin to ensure the feature is low noise [24]. A previous study shows that high right parietal beta or frontal alpha power correlates to high valence [25]. Positive emotion indicates high left frontal activation, while negative indicates high right frontal activation [26].

Computer analysis of non-invasive recording characteristics for autistic patients, such as magnetoencephalography, has become more effective and demonstrates huge diagnostic potential [27]. A common feature of these technologies is the use of feedback from individual bioelectrical characteristics of patients in the organization of therapeutic interventions to achieve extreme personalization [28]. There are five EEG bands which are delta (0–4 Hz), theta (4–8 Hz), alpha (8– 12 Hz), beta (12–30 Hz), and gamma (30-42 HZ), but these band definitions will differ between researches. These frequencies represent different functions and states of the brain. Other states have specific cortical topography, process, and physiology [29].

A clinical EEG sensor is used to determine emotions with high accuracy. Still, due to its time-consuming setup process and sensitivity to noise, it is most suitable for use in clinical settings. Besides the high accuracy of emotion classification, the other advantage of clinical EEG-based emotion classification is fast response time. Also, it allows for collecting data on impaired patients such as facial paraplegia or lack of facial emotional expression [26].

Nevertheless, clinical EEG also has some limitations, which are long setup times compared to other emotion classification methods[30]. The size of the clinical EEG is large and restricts the location (lab) to collect or test the data. The clinical EEG will increase the nervousness of autistic patients since the clinical EEG needs to wrap the head with clinical EEG. Thus, more people prefer dry EEG to wet EEG [31]. Although the portable EEG sensor has lower accuracy than the clinical EEG sensor, most autistic patients prefer wireless and small EEG sensors to clinical EEG sensors [32]. Thus, this research will use a portable EEG sensor to investigate the EEG signal difference between typically developing people and autistic patients with different emotions.

2.0 METHODOLOGY

This study is divided into four main domains: EEG signal acquiring, EEG signal preprocessing, EEG signal feature extraction, and emotion classification. There are a few main stages to analyzing subjects' EEG signals in this study in different emotions. Firstly, a portable EEG sensor, MUSE 2, is used to acquire subjects' EEG signals. Then, preprocess the EEG signals with an adjustable notch filter, decision tree, and Fourier transform to ensure there was no noise before analyzing the signal. After preprocessing the signal, feature selection methods such as Chi-square, t-test, ReliefF, and principal component analysis (PCA) will be applied to select important features. Lastly, several machine learning methods will be applied to classify the emotions of the ASD group.

2.1 Acquire Raw EEG Data

The portable EEG Sensor (MUSE 2 from InteraXon Inc.) was used in this research to measure the brainwaves of autistic patients, such as Alpha, Beta, Theta, Gamma, and Delta waves. In addition, the sensor is also able to measure heart rate (PPG + pulse oximetry), body position (accelerometer), and breath rate (PPG + gyroscope). Figure 1 shows the location of the electrodes in MUSE 2 and MUSE EEG headset electrodeposition.

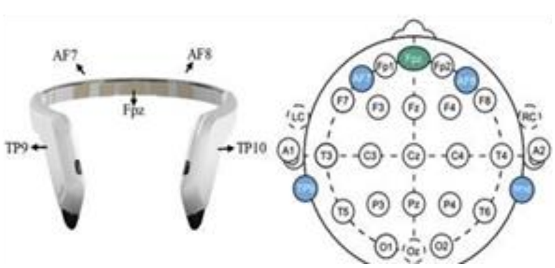

Figure 1 (a) Location of electrodes in MUSE 2 sensor (b)MUSE EEG headset electrodeposition [33]

The EEG signals were recorded using four electrode pads which are TP9, AF7, AF8, and TP10, with Fpz as a reference. The facial emotion of each participant was observed, and the recorded outputs were based on the facial emotion expression. The cheerful emotion data collection will be conducted twice to ensure the dataset's consistency. Before data collection, the headband was worn tightly on the subject's head but did not cause any uncomfortable to the subjects.

The subjects were requested to watch a 10-minute favorite video to stimulate positive emotion (joy and happiness) [34] until 500 positive emotion outputs for each subject. After collecting the positive emotion EEG signal data, the subject collected the neutral emotion (bored) [34] signal data after one hour's rest. Next, the subjects requested to watch 10 minutes of boring or not exciting videos based on the survey form (prevent emotional fluctuation) to collect 500 neutral emotion outputs. After neutral emotion data collection, the above steps were repeated by replacing boring videos with sad or dislike videos based on the survey form, and the negative emotions (fear, anger, sadness, and disgust) [34] in the dataset were produced.

The selection of 20 subjects for EEG signal collection was carefully detailed to ensure consistency and reliability. Table 1 indicates participants were divided into two groups: 10 individuals with ASD and 10 age and gender-matched TD individuals with no history of neurological or psychological disorders. The age range was set between 12 and 30 years to maintain a consistent developmental stage, with an almost equal representation of males and females to account for gender-based neural differences.

Table 1 Volunteer Demographics Characteristic

Demographic Characteristic	Component	ASD	TD
Gender	Male	5	5
	Female	5	5
Age	Below 12	3	3
	12-18	2	2
	18-21	3	3
	21-30	2	2

Exclusion criteria included a history of epilepsy, head trauma, neurological disorders, or the use of medications affecting neural activity. Additional demographic and behavioral factors such as handedness, cognitive abilities, and emotional responsiveness were assessed to control for variability. EEG recordings were conducted in a quiet, controlled environment, with participants adhering to pre-session guidelines to reduce external influences, such as avoiding caffeine or excessive screen time. These criteria ensured a balanced and representative sample while minimizing confounding variables, enhancing the validity and reproducibility of the study.

2.2 EEG Signal Preprocessing

Before feature extraction and emotion classification, the EEG signal data were preprocessed by using a noise filter to remove the noise. MUSE 2 headbands can provide preprocessed or raw EEG signal data. The original or natural MUSE 2 EEG data was applied adjustable notch filter (narrow band stop filter or band rejection). This filter can remove 45 to 64 Hz frequency when the EEG signal passes through MUSE 2 headbands.

In MUSE 2, by over-sampling and then down-sampling to obtain a 256Hz output sampling rate of 2uV (RMS) noise, a preprocessed signal with noise-free and high computational efficiency can be received. An active noise filter or cancellation was accomplished using an onboard-driven right leg (DRL) between the Fpz and frontal electrodes. To ensure the EEG electrode contacts the skin properly and removes the electrode noise, a feedback circuit (DRL) is designed.

The decision tree was used to identify whether the signal is noise or clean movement based on the characteristics of the incoming EEG signal, i.e. kurtosis, variance, and amplitude. For the low amplitude, variance kurtosis signals were considered clean data and well in contact with the subject skin. The onboard signal processing module used Fourier transform (90% overlap and 256 samples window size) on EEG raw data to obtain the frequency bands. The five EEG frequency bands are delta, theta, alpha, beta, and gamma.

2.3 EEG Signal Feature Extraction

The feature extraction process is useful to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Also, the reduction of the data and the machine's efforts in building variable combinations (features) facilitate the speed of learning and generalization steps in the machine learning process. To test the probability of each EEG band in different emotions, the T-test was used in this study.

2.3.1 T-test

The T-test is one of the common statistical analysis methods to identify the difference between two data sets. The T-test is also one of the hypothesis tests to differentiate whether a set of scores is from a different population. There are three types of t-tests: two samples t-test, paired samples T-test, and one-sample T-test. This study used a two-sample t-test to justify the features with significant differences between different emotions.

A two-sample T-test is a commonly used hypothesis test to determine or compare the average difference between two sample groups (due to random chance or significant average difference).

2.4 EEG Signal Analyze

After EEG signal feature extraction, the dataset is saved as an Excel file for further analysis using Python. The unwanted reading will be removed. The dataset is labeled based on the current emotion. In this experiment, 20 parameters were collected, namely Alpha waves (TP9, TP10, AF7, and AF8), Beta waves (TP9, TP10, AF7, and AF8), Gamma waves (TP9, TP10, AF7, and AF8), Theta wave (TP9, TP10, AF7, and AF8), Delta wave (TP8, TP9, AF7, and AF8). The average of each EEG band is calculated as

$$\text{Average Frequency} = (x2+ x2+ x2+x2)/4 \quad (1)$$

Where x1 represents the frequency band at AF7, x2 represents the frequency band at AF8, x3 represents the frequency band at TP9, and x4 represents the frequency band at TP10. At the end of the process, each frequency band's average will be obtained and saved in an Excel format, i.e. XLS, for further classification. The average EEG band signal will be used to compute the difference between the ASD and TD groups.

3.0 RESULTS AND DISCUSSION

To understand the EEG band signal difference of the ASD group in different emotions, the EEG band signal for the ASD group in different emotions was computed. The EEG signal from 4 electrodes was collected and analyzed individually.

3.1 EEG Bands Signals Difference for ASD Group in Different Emotion

To investigate the difference in EEG band signal for the ASD group in different emotions, an independent t-test was conducted to assess the statistical significance of the difference, as presented in Table 3. There were 10 samples of the ASD group for each EEG band in three different emotions. Table 2 summarizes the EEG band activity observed in the ASD group under different emotional responses.

Table 2 Result of EEG Band Signals for ASD Group

EEG Band	Emotions	Electrode			
		TP9	AF7	AF8	TP10
Alpha	positive	0.5775	0.3419	0.8565	1.1478
	neutral	0.4894	0.2429	0.7629	1.0440
	negative	0.4823	0.2351	0.7452	1.0063
Beta	positive	0.0122	0.7132	0.4886	0.9810
	neutral	-0.0730	0.6920	0.4753	0.9412
	negative	-0.1650	0.6561	0.4554	0.8867
Delta	positive	0.9838	1.3571	0.1347	0.6431
	neutral	0.9039	1.2753	0.0794	0.5248
	negative	0.9111	1.3116	0.0580	0.5254
Theta	positive	1.3291	0.1228	0.7213	0.4918
	neutral	1.3093	0.1160	0.6451	0.4215
	negative	1.2305	0.0316	0.6661	0.4522
Gamma	positive	0.3955	0.9154	1.2012	0.0522
	neutral	0.2743	0.7932	1.0686	-0.0450
	negative	0.2673	0.1489	1.0346	-0.1320

Table 3 T-test Result for ASD Group

EEG Band	Electrode	P-Value		
		Positive and Neutral	Positive and Negative	Neutral and Negative
Alpha	TP9	**	**	ns
	AF7	**	**	ns
	AF8	**	**	**
	TP10	**	**	**
Beta	TP9	**	**	**
	AF7	**	**	**
	AF8	**	**	**
	TP10	**	**	**
Delta	TP9	**	**	ns
	AF7	**	**	**
	AF8	**	**	**
	TP10	**	**	ns
Theta	TP9	**	**	**
	AF7	ns	**	**
	AF8	**	**	**
	TP10	**	**	**
Gamma	TP9	**	**	ns
	AF7	**	**	ns
	AF8	**	**	**
	TP10	**	**	**

3.1.1 Alpha EEG Band

The Alpha wave in all electrodes for the ASD group in positive emotions is higher than in other emotions. The Alpha wave at TP9 and AF7 was not suitable for classifying the neutral emotion and negative emotion of the ASD group because the Alpha wave for neutral feeling and negative emotion was not significant. The amplitude of ASD group has the highest amplitude of the Alpha wave in the joyful environment based on the result, while the negative sentiment has the lowest amplitude of the Alpha wave. There was an increase in Alpha wave amplitude when our brain spent periods of relaxation due to brain waves becoming slower [39]. Thus, in a relaxed environment, the autistic patient will have higher positive emotions and alpha waves than in a dull or nervous environment.

3.1.2 Beta EEG Band

Beta wave for the ASD group in positive emotion was significantly higher than neutral and negative emotions. The difference in amplitude between different emotions for the ASD group Beta wave is significant ($p < 0.05$). Beta waves are associated with active thinking, intense brain activity, and focus, among other emotions or circumstances [40]. Humans have higher beta wave amplitude when attention to some things. Therefore, the beta wave of the ASD group in positive emotions was higher than in other emotions. It was due to the autistic patient having high concentration and attention while enjoying a favourite activity.

3.1.3 Delta EEG Band

The intermediate delta wave at electrodes TP9 and TP10 for neutral and negative emotions was not substantial for classifying both emotions. The amplitude of the delta wave for the ASD group in positive emotion recorded the highest amplitude compared to other emotions. The delta wave would have a high amplitude [39]. Thus, autistic patients have high amplitude when enjoying interesting videos or activities. The autistic patient does not focus on a neutral or negative emotion, which causes the delta wave amplitude to be lower than positive emotion. The TD group also indicates that the average delta wave in positive emotion was higher than negative because TD people were more focused in a positive environment.

3.1.4 Theta EEG Band

The ASD group recorded lower amplitude in neutral and negative emotions compared with the ASD group in positive emotions. Theta wave was suitable to use for emotion classification except for theta wave at electrode AF7. Low amplitude theta waves were due to drowsiness and decreased alertness, while high amplitude theta waves are associated with memory function [38]. Autistic patients have low memory function when they feel dull, scared, angry, or sad. Thus, to improve autistic patients' learning curve, a joyous atmosphere can improve autistic patients' memory function.

3.1.5 Gamma EEG Band

The gamma wave amplitude for the ASD group in positive emotions was higher than for neutral and negative emotions. All EEG band signals have significant differences ($p < 0.05$) in all electrodes except electrodes at TP9 and AF7. The gamma wave at four electrodes for the ASD group in a joyful environment is higher than the ASD group in other emotions due to the low concentration of the inhibitory neurotransmitter GABA, which is also associated with ASD [41]. Gamma wave was associated with memory, learning, and motor movement [40]. The gamma wave amplitude is mainly related to the subject's decision-making, which involves motor function, matching, and memory [42]. For example, the autistic patient would try to memorize the current scene when excited and attempt to neglect the tragic scene. Besides, the difference between positive, neutral, and negative emotion was significant and able to assist the researcher in classifying the emotion of the ASD group except for the Gamma wave at TP9 and AF7.

3.2 EEG Bands Comparison for ASD Group and TD. Group

There was a total of 20 parameters performed in this section. T-test has been used to investigate and justify the significant difference between the two groups. The average of each EEG band is analyzed after collecting all EEG signals, as shown in Table 4. To understand the difference between the ASD group and the TD group in terms of EEG signal, a t-test analysis method was used. The average of each EEG band will be used for t-test analysis. A total of 20 samples (10 ASD individuals and 10 TD individuals) were participants in this experiment.

Table 4 Comparison between ASD Group and TD. Group

Groups	EEG Band	Emotions		
		Positive	Neutral	Negative
ASD	Alpha	0.7309	0.6348	0.6172
	Beta	0.5487	0.5088	0.4583
	Theta	0.6662	0.6229	0.5951
	Delta	0.7796	0.6958	0.7015
	Gamma	0.7520	0.7120	0.7120
TD	Alpha	1.1489	1.2743	0.8329
	Beta	1.1217	1.2794	0.7872
	Theta	1.5462	1.5221	1.1911
	Delta	1.2965	1.1762	0.8341
	Gamma	0.9050	1.0207	0.5494

3.2.1 *Positive Emotion*

The average of all EEG bands for the TD group is higher than the ASD group and recorded more than 1mV, except for the Gamma wave. Meanwhile, the ASD group indicates that all EEG band average amplitude is lower than 1mV. The average EEG band of the ASD group in positive sentiment is lower than the TD group for all EEG bands. Besides, it indicates that there are significant differences between the ASD group and the TD group ($p < 0.05$). For positive emotion, all EEG signals (alpha, beta, delta, theta, and gamma EEG band) of the ASD group are lower than the TD group. It is due to ASD volunteers being unable to relax when unfamiliar people are in the room entirely. The previous study indicated a significant association between anxiety and social deficits or social communication skills in autistic children [43, 44]. ASD patients would have a sense of oppression and loss of focus, while the TD group could communicate or conduct the study as usual.

3.2.2 *Neutral Emotion*

The average EEG band signal for the ASD group is lower than 0.8mV, while the average EEG band signal for the TD group recorded more than 1mV. Besides, it also indicates that there is a significant difference between the TD group and the ASD group ($p < 0.05$) for the average of EEG band signals in neutral emotion. Meanwhile, all EEG signals of the ASD group are lower than the TD group, especially the beta wave and gamma wave in neutral emotion. Low amplitude of beta waves was usually associated with learning disabilities, brain damage, and attention. This power behavior of the beta wave shows that the subjects' positive thinking and concentration are weakened, which may lead to a decrease in vigilant watch [45]. The ASD group would reduce attention to the video while the TD group attempted to focus on the video, although the video was boresome. Gamma waves appear during short-term memory matching between visually identifiable elements and other sensory stimuli [46]. ASD group lost concentration when watching a boring video. Thus, the ASD group did not link the current scene with their previous experience or video. As a result, ASD group volunteers could not memorize the content of the boring video after the study.

3.2.3 *Negative Emotion*

For negative emotion, all average EEG band amplitudes for the ASD group have significant differences compared with the TD group ($p < 0.05$). Furthermore, the average EEG band amplitude for the ASD group is higher than the TD group except for the gamma wave. The delta wave and theta wave for the ASD group are almost similar to the TD group in negative emotion. The Theta wave was associated with the subject's voluntary inhibition of the stimulus-response because it is found that the theta wave will increase when the individual intentionally inhibits the response [47]. Thus, ASD and TD group volunteers will attempt to bottle up their own emotions and cause the theta wave to have a high amplitude of negative emotion. Delta wave oscillations are related to the synchronization of brain activity and autonomous functions, motivational processes related to reward and disrespect for defense mechanisms, higher emotional participation, and recognition related to significant stimuli that detect attention and cognitive motivation [48]. For example, ASD and TD group volunteers are more emotional when watching or listening to a nasty video. However, the average gamma-band signal for the ASD group in negative emotion is lower than the TD group. The ASD group will take longer to recover their emotion than the TD group. The gamma wave controls cognitive functions such as learning, memory, and information processing. The presence of this wave causes anxiety, increased alertness, and stress.

4.0 CONCLUSION

The study revealed significant differences in EEG band amplitudes between ASD and TD groups, indicating distinct neural activity patterns. Existing emotion classification models based on TD data are unsuitable for ASD individuals. The ASD group showed higher alpha wave amplitudes in relaxed and cheerful states, suggesting improved learning curves in positive environments. Gamma waves were notably distinct across emotions in ASD, highlighting their importance for emotion classification. While no significant differences were found between TP9 and AF7, 13 of 20 EEG features were significantly different, supporting their use for classifying ASD emotions. Tailored models could aid therapy by addressing ASD-specific neural patterns.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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