Tensor factorization approach for ERP-based assessment of schizotypy in a novel auditory oddball task on perceived family stress

Ahmad Zandbagleh[1], Sattar Mirzakuchaki[1,*], Mohammad Reza Daliri[1], Preethi Premkumar[2], Luis Carretié[3] and Saeid Sanei[4]

[1] School of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran
[2] Division of Psychology, School of Applied Sciences, London Southbank University, London, UK
[3] Facultad de Psicología, Universidad Autónoma de Madrid, 28049 Madrid, Spain
[4] School of Science and Technology, Nottingham Trent University, Clifton Lane, Nottingham, UK

* Corresponding author.
E-mail: m_kuchaki@iust.ac.ir

Abstract

Schizotypy, a potential phenotype for schizophrenia, is a personality trait that depicts psychosis-like signs in the normal range of psychosis continuum. Family communication may affect social functioning in people with schizotypy. Greater family stress, such as irritability, criticism and less praise, is perceived at a higher level of schizotypy. This study aims to determine the differences between people with high and low levels of schizotypy using electroencephalography (EEG) during criticism, praise and neutral comments. EEGs were recorded from twenty-nine participants in the general community who varied from low schizotypy (LS) to high schizotypy (HS) during a novel emotional auditory oddball task. We consider the effect of event-related potential (ERP) parameters, namely the amplitude and latency of P300 subcomponents (P3a and P3b), between pairs of mood descriptors (standard, positive, negative and neutral). A model based on tensor factorization is then proposed to detect these components from the EEG using the CANDECOMP/PARAFAC (CP) decomposition technique. Finally, we employ the mutual information estimation method to select influential features for classification. The highest classification accuracy, sensitivity, and specificity of 93.1%, 94.73%, and 90% are obtained via leave-one-out cross validation. This is the first attempt to investigate the identification of schizotypy by finding brain responses that are specifically associated with perceiving family stress and schizotypy. By measuring these responses, we achieve the goal of improving the accuracy in detection of early episodes of psychosis.

Keywords: EEG, electroencephalography, event-related potentials, P300 subcomponents, schizotypal personality disorder, schizotypy, tensor decomposition

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1. Introduction

Schizotypy is latent organization of personality traits, where people do not have psychosis, but occasionally have psychosis-like signs, such as paranormal beliefs, referential thinking and disorganized speech [1]. Yet, it is debatable as to whether schizotypy is a forerunner of psychosis [2]. Schizotypy is characterized by cognitive, emotional, and perceptual deficits, which correlate with schizophrenia spectrum impairments [3]. It is agreed that schizotypy includes three dimensions, namely positive (paranormal perceptual experience, unusual beliefs, delusional beliefs), negative (reduction of interest in physical and social activities), and disorganized (bizarre behavior or speech) [4]. Family stress is a serious risk factor that increases the risk of onset of psychosis [5]. People with schizotypy may not seek help for family stress because they do not recognize that the family stress can make them susceptible to the future onset of psychosis [6, 7]. People with schizotypy are less prone to suffer future psychosis if their carer is supportive and expresses praise and acceptance. Good family communication is vital for mental health, as it allows people to understand each other and sustain social support [8]. So, more research is needed into how family stress increases vulnerability for psychosis. It might provide the relation between schizotypy and family stress.

Electroencephalography (EEG) signals have been used to diagnose and predict mental disorders by means of advanced signal processing techniques in recent years [9], including the risk for psychosis [10, 11]. Event-related potentials (ERPs) are early attention brain responses to various stimuli [12, 13]. Certain ERP components are atypical in patients with psychosis and people at risk of psychosis, and they are good biomarkers of mental dysfunctions, including schizophrenia [14, 15]. The P300 component of ERPs reflects a variety of cognitive processes, although attention and memory (context updating) have been stressed as those contributing to a greater extent to its amplitude [16]. With regards to attention to the stimulus, different aspects are reflected in the two P300 subcomponents, namely P3a and P3b. P3a reflects stimulus-driven attentional capture (or automatic attention) and is anteriorly distributed [17]. P3b is posteriorly distributed and denotes sustained attention and top-down control detection of relevant events [16-18]. In contrast to P3b, P3a is independent of the task [19, 20]. P300 latency indicates speed of processing.

Studies have employed emotion or cognition tasks to elicit ERP components for evaluating schizotypal personality disorder (SPD) [21-28] or schizotypy [29-33]. The auditory oddball task is adept at evoking the P300 response. In it, the participant's attention is alerted to an infrequent or 'deviant' stimulus appearing in the form of a higher auditory tone in 20% of the trials, whereas the rest of stimuli (80%) consist of low tones and cause attentional habituation. P300 amplitude is maximal in response to infrequent targets in the general population [16]. Individuals diagnosed with SPD show reduced P300 amplitude during the traditional auditory odd-ball task in information processing [21, 22]. Individuals at high risk for psychosis, especially those who subsequently convert to psychosis, also show reduced P300 amplitude to the infrequent stimulus than healthy individuals [17]. Kutcher and colleagues have shown that the P300 latency during oddballs is longer in SPD individuals than in normal cases [23], suggesting slower speed of processing of the target stimulus. Some studies [24, 25] have suggested that schizophrenia patients have a lower P300 amplitude than normal individuals in the auditory oddball task, whereas the SPD individuals have an intermediate P300 amplitude [25]. Vohs et al. [26] used a visual line-orientation discrimination task to compare schizophrenia, SPD, and normal individuals. They found that the schizophrenia patients have a smaller P3a amplitude and extended P3b latency compared to normal individuals. There are no significant differences between SPD and either group in P300 subcomponents' amplitude and latency. Increased P300 amplitude has also been found in a visual oddball task among individuals at risk for psychosis with co-morbid autistic spectrum disorder [34], suggesting that abnormally high P300 is also a risk factor for conversion to psychosis. Another study [29] showed that greater P300 amplitude when passively watching scenes depicting rejection is associated with greater negative schizotypy.

Examining the P300 response to a social cognition oddball task would likely allow detection of attention impairment arising from social anxiety in schizotypy [30]. Altered neural and physiological responses to social interactions [6, 29, 30] substantiate social anxiety in schizotypy. People with schizotypy have lower-than-normal activity in the insula when listening to a close relative's praise, implying lack of reward from praise [6]. Given the heightened sensitivity to family stress in schizotypy [6, 7], we designed a novel semantic oddball task in this study where the word 'normal' was the frequent standard stimulus and it followed criticism, praise and neutral comments for the majority (75%) of trials. The infrequent stimulus (25% of trials) was a mood-congruent word, e.g., 'rage' followed criticism, 'happy' followed praise and 'time' followed neutral comments. In this novel social cognition oddball task, increased P300 amplitude is hypothesised when oddballs (negative words) follow criticism because of the heightened sensitivity to criticism in schizotypy. Other semantic lexical processing tasks also elicit the N400 ERP component in schizotypy. One study [31] displayed increased N400 amplitude during both visual and auditory lexical processing tasks in individuals with SPD relative to healthy individuals. In contrast, a decrease in N400 amplitude has been reported in females with SPD in visual semantic processing tasks [28] and it suggested overactivation, possibly implying disinhibition, of the semantic network because of greater ease of gaining access to words within semantic memory. Del Goleto et al. [31] designed an experiment in which individuals read short stories ending with either a literal, ironic or incompatible statement. They found that low schizotypy (LS) individuals elicited reduced N400 amplitudes after literal targets compared to incompatible targets during semantic context task that suggests diminished semantic processing. In contrast, the high schizotypy (HS) group did not produce this effect which suggests an impairment in lexical processing in HS [32]. Similar to schizophrenia patients, one study [33] suggested the theory of mind (ToM) impairment with a lower P300 amplitude in the schizotypy group. They showed that schizotypy individuals had lower P300 amplitude in responding to positive, negative, and neutral ToM tasks. Thus, both elevated and reduced amplitudes are seen for attention-processing (P300) and semantic-processing (N400) ERPs during social cognition tasks in individuals with HS or schizotypal personality.

Sophisticated EEG-based signal processing and machine learning research to classify HS and LS is scant in the schizotypy literature. One study [35] reached zero false-positive rate by using shrinkage linear discriminant analysis (SKLDA) to classify HS and normal groups during an audio-visual emotion processing task. Some studies used functional/effective brain connectivity to distinguish between schizotypy groups. Including one [36] which achieved an accuracy of 74.3% in their proposed method. They examined a combination of features including weighted phase lag index (wPLI) as a measure of brain connectivity to distinguish between two schizotypy groups. Quite recently, the authors have used directed transfer function (DTF) derived from multivariate autoregressive (MVAR) coefficients and achieved an accuracy of 89.21% to effectively classify the subjects into HS and LS categories for the first time [37].

Recently, tensor decomposition as a multi-dimensional component analysis has become an attractive tool in signal processing [38-41]. In this study, an algorithm based on tensor factorization is proposed to analyze the P300 subcomponents, namely P3a and P3b. We use a third-order tensor with three slabs, namely channel, time, and trial. Then, the tensor is decomposed into temporal, spatial, and trial component factors using the CANDECOMP/PARAFAC (CP) decomposition technique for statistical analysis of results in two steps. In the first step, we aim to examine significant differences in P300 subcomponents between pairs of mood descriptors within each group. In the second step, the significant differences are determined in P300 subcomponents between HS and LS groups for each mood descriptor. Finally, the mutual information is estimated for the features acquired using spatial and temporal factors to select influential features. Three types of popular classifiers, namely linear discriminant analysis (LDA), support vector machines (SVM), and decision tree (DT) are used to evaluate the proposed method. On the other hand, a fourth-order tensor in the channel, time, trial, and subject is employed for better visualization of detected P300 subcomponents.

The present study answers two main questions: (1) how do the ERP brain responses to emotional stimuli depicting family stress differentiate between HS and LS people, and (2) how accurately can the proposed method distinguish people with schizotypy from people with no schizotypy in the sub-clinical population and hence, qualify as a biomarker? It is hypothesized that: (1) P3b to deviant target words is larger than to standard (always neutral) target words only if the formers are emotional and congruent, but not if they are neutral and incongruent, (2) P3a amplitude does not significantly differ between deviant target and standard target words, (3) individuals with HS have higher P3b amplitude during deviant target words that follow criticism and praise than individuals with LS. The differences between HS and LS in P3a and P3b latencies were also measured for exploratory purposes.

2. Material and methods

2.1 Participants

Fifty participants, including 25 HS and 25 LS (age range 18-48 years) were screened from the general population in Nottingham Trent University (NTU) using methods that successfully recruit HS and LS participants, namely placing adverts on social networking websites and community centers for people with spiritual or paranormal beliefs, and the local newspaper. People with HS are those who obtained a score above 31 (out of 74) on the Schizotypal Personality Questionnaire (SPQ) [42]. People with LS are defined as those obtaining a score below 13 (out of 74) on the same questionnaire. These scores denote that people with scores in the 90th and 10th percentiles of the SPQ have HS and LS, respectively [43]. Finally, 19 HS and 10 LS individuals have been selected for the analysis step. Table 1 demonstrates the demographic characteristics and scores based on the SPQ.

2.2 Emotional oddball task

This task aims to determine whether people attend to a deviant target word (e.g., ‘happy’) more than a standard neutral target word (‘normal’) after listening to personal remarks (e.g., praise and criticism). The standard neutral target word, ‘normal’, appeared on the computer screen in 75% of trials (standard trials) so that the participants habituate to the word ‘normal’ in the majority of trials. Positive, negative, or neutral mood descriptors appeared as the deviant target word in 25% of trials. The sequence of events in the standard trials (75% of trials) was as follows: the participants (1) listened to the comment (e.g., praise), (2) saw the pre-target stimulus prime ‘*how does it make you feel?*’ (the introduced interval varied pseudo-randomly between 300 and 650 ms to avoid anticipation of the time when the mood descriptor appeared), (3) observed the standard target ‘normal’ or the mood-congruent deviant (positive, negative, or neutral) word (the target appeared for a second), and then (4) performed ‘Yes’ or ‘No’ with a button-press. Participants could choose ‘Yes’ if they felt that the mood of the target word was congruent to the mood of the comment. A ‘No’ response indicated that the comment and the word were not congruent. In the deviant trials (25% of trials), a positive mood descriptor, e.g., ‘loved’, followed praise. A negative mood descriptor, e.g., ‘afraid’, followed criticism. A neutral mood descriptor, e.g., ‘speech’, followed a neutral comment. Figure 1 illustrates the trial structure of the emotional oddball task.

Table 1. Demographic characteristics and scores [Mean (S.D.)] on the SPQ.

	HS (n=19)	LS (n=10)	F/Chi-square (*df*)	*p-value*
Age	24.79 (8.12)	22.60 (3.31)	0.66 (1,27)	0.424
Gender (male/female)	6/13	5/5	0.99 (1)	0.331
Ethnicity (European-descent/Asian, African, Caribbean or similar ethnicity, other)	17/2	6/4	3.47 (1)	0.063
SPQ total	39.22 (6.38)*	9.10 (4.70)	170.02 (1,26)	<0.001
SPQ cognitive perceptual	18.00 (5.89)*	2.6 (1.95)	63.48 (1,26)	<0.001
SPQ interpersonal	17.39 (5.80)*	5.00 (2.62)	40.45 (1,26)	<0.001
SPQ disorganisation	9.16 (3.47)*	1.90 (2.08)	36.26 (1,26)	<0.001

* Mean (S.D.) based on 18 participants. The SPQ scores were missing for one participant. S.D. refers to standard deviation.

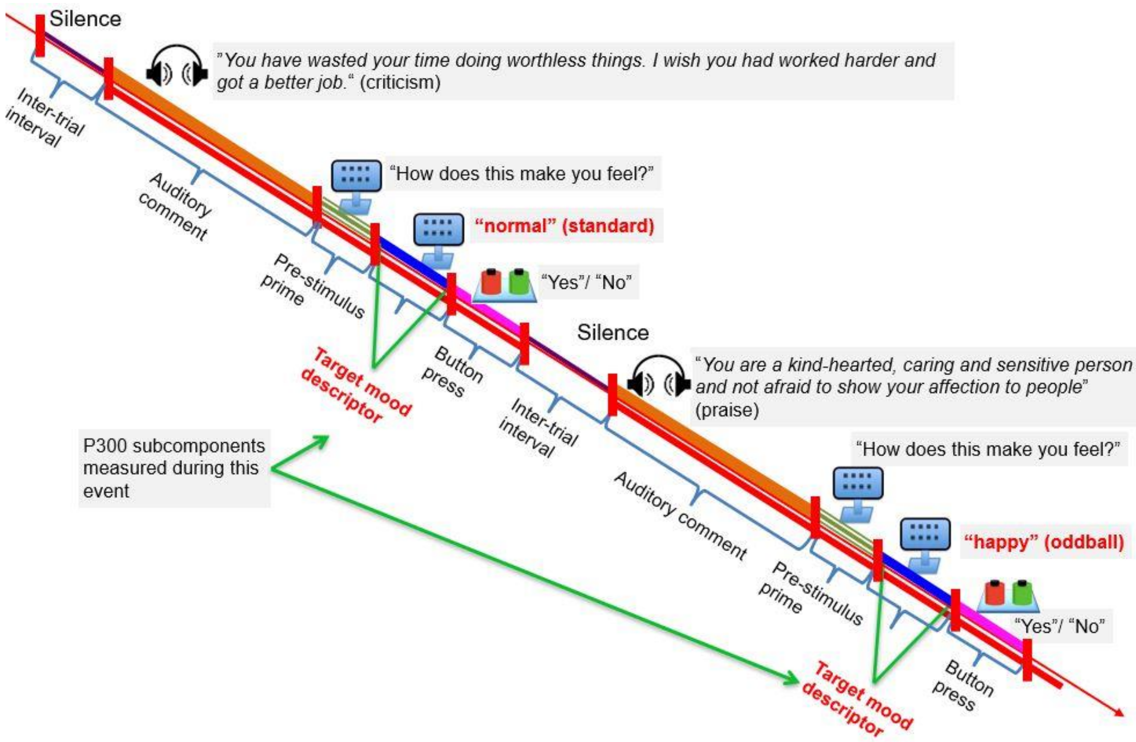

Figure 1. The trial structure of emotional oddball task.

2.3 EEG recording and preprocessing

The EEG was recorded using a BioSemi Active-Two system (Biosemi Inc, Amsterdam, Netherland) by 64 Ag-AgCl active electrodes based on an international 10/20 system and 2048 Hz sampling rate. EEGLAB toolbox [44] running on MATLAB 2019a was used to preprocess the data. All data channels were referenced to the Cz electrode and down-sampled to 256 Hz. Then, the EEG data were filtered using a finite impulse response (FIR) highpass filter at 0.5 Hz and a lowpass filter at 30 Hz with zero phase shift, separately. Subsequently, epochs were extracted from 100 ms before the appearance of the stimulus and 1000 ms after that. After the baseline correction between -100 ms and 0, ERP trials were checked visually to exclude artifacts.

2.4 Tensor decomposition

A tensor is a multiway (N-way) array which contains N vector spaces with its specific coordinate system. Tensor decomposition is a higher-order analogue of the matrix singular value decomposition (SVD), which enables exploitation of the data diversities in different domains to decompose the data into their disjoint components [45]. Tensor decomposition, as a state-of-the-art method in signal processing and neuroscience, has been widely used in the past two decades for biosignal analysis [38-41]. In this study, we have used one of the most popular types of tensor decomposition, namely the CP decomposition algorithm. Before giving a brief description of the CP algorithm and its optimization, the notation and mathematical terminology are explained.

2.4.1 Notation and terminology

In this study, all the notations have been adopted from [46]. The number of tensor dimensions is defined as tensor order. Lowercase letters indicate scalars, e.g., a. Boldface lowercase letters denote vectors, e.g., $\mathbf{a}$. Boldface capital letters refer to matrices, e.g., $\mathbf{A}$. Boldface Euler letters show high-order tensors (high-way arrays), e.g., $\boldsymbol{\mathcal{Y}}$. The *i*th column of $\mathbf{A}$ matrix is defined by $\mathbf{a}_i$, compactly. $\mathrm{A}^{(n)}$ is defined as the *n*th matrix in a sequence. $\boldsymbol{\mathcal{Y}}_{(n)}$ is defined the mode-n matricization of a tensor $\boldsymbol{\mathcal{Y}} \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}$ .The symbols $\circ$,$*$, and $\odot$ denote vector outer product, elementwise product, and Khatri-Rao product, respectively. The Kruskal operator is denoted by $[\![\;]\!]$.

2.4.2 CP-optimization

The CP decomposition converts an input tensor into a sum of rank-one components, which is defined as (R denotes the number of components):

$$\boldsymbol{\mathcal{Y}} \approx [\![\mathbf{A}^{(1)},\ \mathbf{A}^{(2)}, \ldots,\ \mathbf{A}^{(N)}]\!] \equiv \sum_{r=1}^{R} \mathbf{a}_r^{(1)} \circ \mathbf{a}_r^{(2)} \circ \cdots \circ \mathbf{a}_r^{(N)} \quad (1)$$

where $\mathbf{a}_r^{(n)} \in \mathbb{R}^{I_n}$ for n=1, ..., N, and r=1, ..., R. $\mathbf{A}^{(n)}$, the factor matrices in different modes, are defined as follows:

$$\mathbf{A}^{(n)} = [\mathbf{a}_1^{(n)}\ \mathbf{a}_2^{(n)}\ \ldots\ \mathbf{a}_R^{(n)}] \quad (2)$$

where $\mathbf{A}^{(n)} \in \mathbb{R}^{I_n \times R}$ for n=1, ..., N, and I_n is the size in mode-n. The matrix form of $[\![\mathbf{A}^{(1)},\ \mathbf{A}^{(2)}, \ldots,\ \mathbf{A}^{(N)}]\!]$ can be expressed as follows:

$$([\![\mathbf{A}^{(1)},\ \mathbf{A}^{(2)}, \ldots,\ \mathbf{A}^{(N)}]\!])_{(n)} = \mathbf{A}^{(n)}(\mathbf{A}^{(-n)})^{\mathrm{T}} \quad (3)$$

where

$$\mathbf{A}^{(-n)} \equiv \mathbf{A}^{(N)} \odot \cdots \odot \mathbf{A}^{(n+1)} \odot \mathbf{A}^{(n-1)} \odot \cdots \odot \mathbf{A}^{(1)} \quad (4)$$

The least-square optimization problem is used for fitting CP problem formulation, so we have

$$\min_{\mathrm{A}^{(1)}, \mathrm{A}^{(2)}, \ldots, \mathrm{A}^{(N)}} f \equiv \frac{1}{2}\left\|\boldsymbol{\mathcal{Y}} - [\![\mathbf{A}^{(1)},\ \mathbf{A}^{(2)}, \ldots, \mathbf{A}^{(N)}]\!]\right\|^2 \quad (5)$$

For solving this problem, the alternating least square (ALS) method has been suggested by Harshman [47]. Some procedures have been developed for improving the efficiency of ALS. In this study, a gradient-based approach has been employed for CP optimization that extracts all factor matrices simultaneously. The partial derivatives of the cost function f are calculated to obtain the gradient with respect to each $\mathbf{a}_r^{(n)}$. So, we have

$$\frac{\partial f}{\partial \mathbf{a}_r^{(n)}} = -\left(\boldsymbol{\mathcal{Y}} \times_{\substack{m=1 \\ m \neq n}}^{N} \mathbf{a}_r^{(m)}\right) + \sum_{\ell=1}^{R} \gamma_{r\ell}^{(n)} \mathbf{a}_\ell^{(n)},$$

for n=1, ..., N, and r=1, ..., R. (6)

where

$$\gamma_{r\ell}^{(n)} \equiv \prod_{\substack{m=1 \\ m \neq n}}^{N} \mathbf{a}_r^{(m)\mathrm{T}} \mathbf{a}_\ell^{(m)} \quad (7)$$

The matrix form of Eq. (6) can be shown as:

$$\frac{\partial f}{\partial \mathbf{A}^{(n)}} = -\mathbf{Y}_{(n)}\mathbf{A}^{(-n)} + \mathbf{A}^{(n)}\Gamma^{(n)} \quad (8)$$

where

$$\Gamma^{(n)} = \Upsilon^{(1)} * \cdots * \Upsilon^{(n-1)} * \Upsilon^{(n+1)} * \cdots * \Upsilon^{(N)},$$

for n=1, ..., N. (9)

The proofs of Eq. (6) and Eq. (8) have been explained in [46]. In this study, a generic nonlinear conjugate gradient method is used to solve the optimization problem [48].

2.4.3 Detecting P300 subcomponents using CP decomposition

In this study, an automatic method is proposed for detecting P300 subcomponents using CP decomposition. Before tensor construction, each three consecutive epochs are averaged using a stride size of one with overlap (separately for each type of target word), and then concatenated. So, the data size remains almost the same, and the averaging length is not too large to be affected by fatigue or habituation. Then, a three-way tensor $\boldsymbol{\mathcal{Y}} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ is constructed for each of the standard, positive, negative, and neutral mood descriptors. I_1, I_2 and I_3 denote respectively, channel, time, and trial. Factor matrices were acquired after applying CP optimization to tensor $\mathcal{Y}$ as follows:

$$\mathcal{Y} \approx [\![\mathbf{A}, \mathbf{B}, \mathbf{C}]\!] \equiv \sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \tag{10}$$

where $\mathbf{a}_r \in \mathbb{R}^{I_1 \times R}$, $\mathbf{b}_r \in \mathbb{R}^{I_2 \times R}$, and $\mathbf{c}_r \in \mathbb{R}^{I_3 \times R}$ represent respectively, spatial, temporal and trial factors. Figure 2 shows the three-way tensor after CP decomposition.

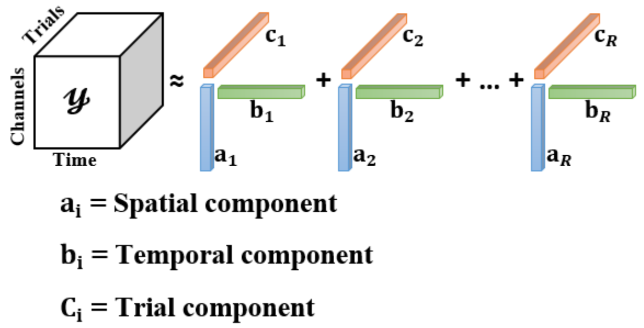

Figure 2. Factorizing three-way tensor using CP decomposition.

After removing the eye-blinking component from temporal factors, four channels (F3, F4, P3, and P4) have been selected based on the typical location of P300 subcomponents. Then, given that P300 is symmetric over centra-lateral brain lobes, the average of each bilateral channel pairs has been taken for further steps. So, the P3a has been quantified as the average signal across F3 and F4 electrodes. A similar approach was used for P3b calculation from the mean value of the spatial components of P3 and P4 electrodes [49, 50]. P3a and P3b components have been selected based on the maximum amplitude within the desired time range (i.e., P3a 200-400ms and P3b 300ms-600ms), after multiplying the remaining temporal and spatial factors. Figure 3 illustrates the entire process of the proposed method in more detail.

In another attempt for a better visualization of the detected ERP components, a four-way tensor $\mathcal{Y} \in \mathbb{R}^{I_1 \times I_2 \times I_3 \times I_4}$ (I_4 corresponds to subject) has been constructed by concatenating subjects' data for each group. So, the CP model is expressed as follows:

$$\mathcal{Y} \approx [\![\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}]\!] \equiv \sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \circ \mathbf{d}_r \tag{11}$$

where $\mathbf{d}_r \in \mathbb{R}^{I_4 \times R}$ denotes subject factor. Finally, to remove the undesired artifacts and for a better illustration, a singular spectrum analysis (SSA)-based filter [51] has been applied to each component.

2.4.4 Statistical analysis

To test hypotheses 1 and 2, a paired sample *t*-test is conducted to determine the significant differences of all HS and LS participants between two pairs of comments including, standard, positive, negative, and neutral mood descriptors.

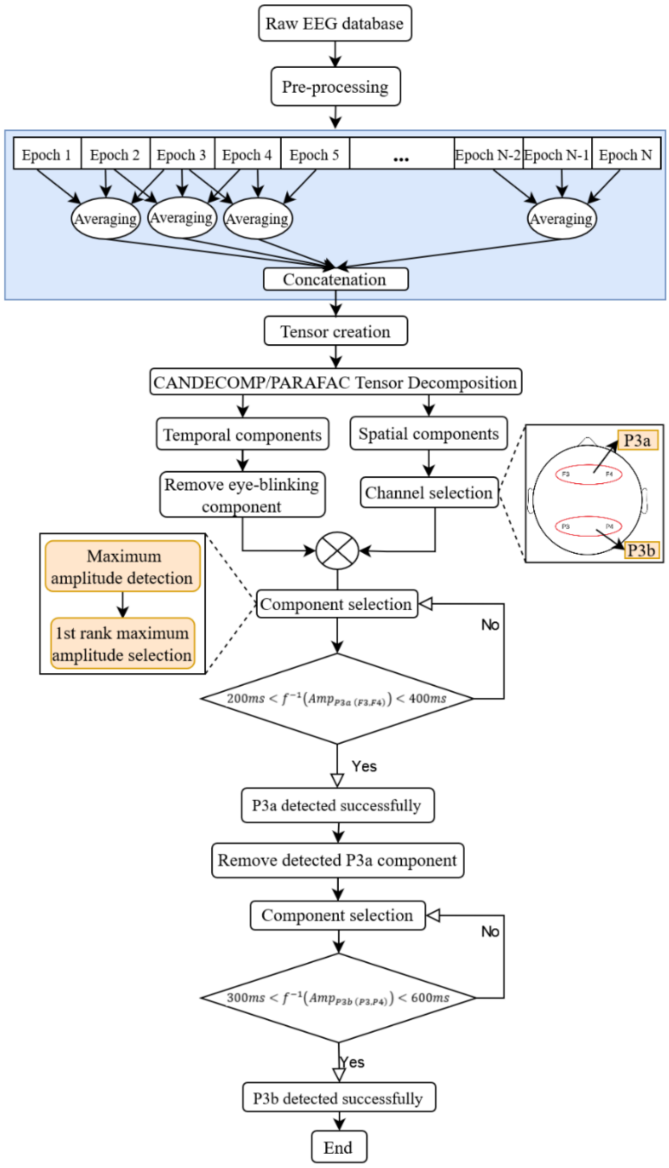

Figure 3. Flow diagram of the proposed method

The significance level for all tests was $P < 0.05$ (two-tailed). To test hypothesis 3, a two-sample *t*-test was applied to determine the significant differences between HS and LS. This analysis was applied between two groups of HS and LS during standard, negative, positive, and neutral mood descriptors.

2.5 Schizotypy classification

2.5.1 Feature extraction

A total of eight ERP components, including P3a and P3b for standard, positive, negative, and neutral mood descriptors were acquired using the proposed method. Additionally, four ERP components that include the whole P300 component in four mood descriptors were obtained using all electrodes, across 200-600 ms, for accurate classification between two groups of schizotypy. Then, the amplitude and latency of these components were extracted as a feature for further processing steps.

2.5.2 Feature selection and classification

Various methods have been proposed in the literature to facilitate classification and selection of the informative features. In this study, estimation of mutual information between features [52], as a filtering technique, is applied to reduce both the redundancy and dimension of features, after selection of significant features using *t*-test. Then, three types of classifiers (LDA, SVM, DT) have been used to distinguish between two groups of schizotypy. In addition to the linear kernel SVM, the polynomial kernel of order 3 has been applied for classification to achieve better performance. The polynomial kernel of order q is defined as [53]:

$$K\left(x_i . x_j\right) = \left(1 + {x_i}^{\mathrm{T}} . x_j\right)^q \tag{12}$$

where x_i and x_j are the feature vectors of two classes.

2.5.3 Performance evaluation

Leave one-out cross validation (LOO-CV) is used to evaluate the model performance. In this approach, the data from N-1 out of N participants are used for training and one for testing. Then, this procedure is repeated for all the participants. Some performance measures namely, accuracy, specificity, sensitivity, and F1-score are derived as follows [37]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{13}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{14}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{15}$$

$$F1 - score = \frac{TP}{TP + \frac{1}{2} \times (FN+FP)} \times 100 \tag{16}$$

where TP is the number of HS participants classified correctly in the HS class, FP is the number of LS participants classified incorrectly as HS class, TN is the number of LS participants recognized correctly in the LS class, and FN is the number of HS participants recognized incorrectly as LS class.

3. Results

3.1 Statistical analysis

In this study, two steps are followed to determine the statistical analysis of the results.

3.1.1 Comparison of amplitude and latency of P3a and P3b between standard and deviant stimuli within HS and LS groups

Table 2 demonstrates the mean amplitude and latency of P3a and P3b for each mood descriptor. Furthermore, the *t*-value and *p*-value of each group's comparisons are shown in Table 2. Evidently, there is a significant increase in P3b amplitude from the standard neutral word (‘normal’) that followed any type of comment to deviant negative mood-congruent words that followed criticism (*t*-value = 3.647, *p*-value = 0.0018) and from the standard neutral word (‘normal’)that followed any type of comment to deviant positive mood-congruent words descriptors that followed praise (*t*-value = 2.401, *p*-value = 0.0273) in the HS group, the difference between negative and positive descriptors being non-significant (P>0.05). With regards to latency of the P3a and P3b ERPs, the results show a significant increase in P3b latency from standard to deviant negative words (*t*-value = 3.334, *p*-value = 0.0037) in HS participants. When comparing the ERP amplitudes between deviant neutral words that followed a neutral comment and any other type of mood descriptors (both standard and deviant) in each schizotypy group, there is a significant increase in P3b amplitude from deviant neutral words to deviant negative words in the HS group (*t*-value = 2.419, *p*-value = 0.0264). Similarly, a significant increase in P3b latency is observed from deviant neutral words to negative deviant words in the HS group (*t*-value = 3.654, *p*-value = 0.0018). There was no significant difference between any other pair of mood descriptors in either HS or LS groups.

In addition, a similar algorithm is produced using a four-way tensor and SSA to better illustrate the P300 subcomponents. Figure 4 shows the comparison between standard and positive mood descriptors for LS and HS groups. Additionally, the comparison between standard and negative mood descriptors for LS and HS groups are illustrated in Figure 5.

3.1.2 Significant differences in P3a and P3b between HS and LS groups during each mood descriptors

Statistical results for comparison between HS and LS groups are reported in Table 3. In contrast to the non-significant findings in standard target word between two groups, there are significant increases in P3b amplitude (*t*-value = 3.401, *p*-value = 0.0021) and latency (*t*-value = 2.161, *p*-value = 0.0397) in negative target word between HS and LS when moving from LS to HS groups. Similarly, the HS has a more significant P3b amplitude than the LS in the positive mood descriptors. (*t*-value = 2.122, *p*-value = 0.0431). There were no such significant relations in any of the other mood descriptors between HS and LS groups.

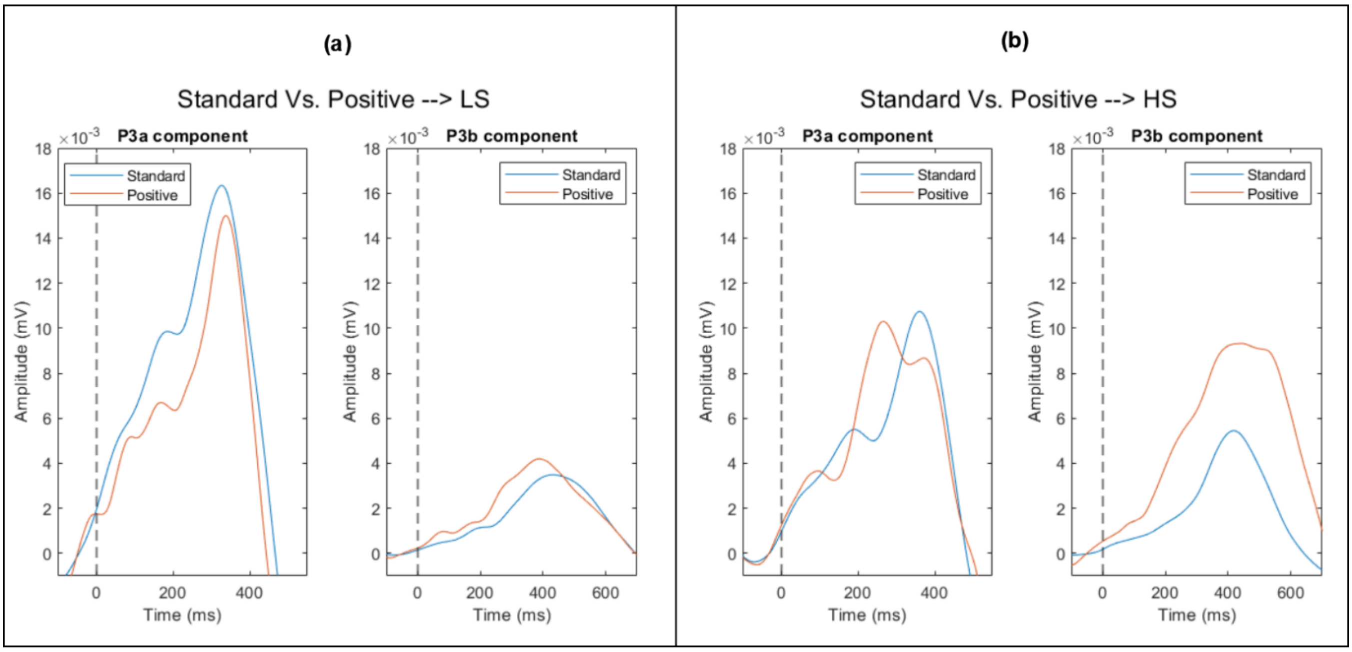

Figure 4. The comparison of P300 subcomponents between standard and positive mood descriptor for LS(a) and HS(b) groups.

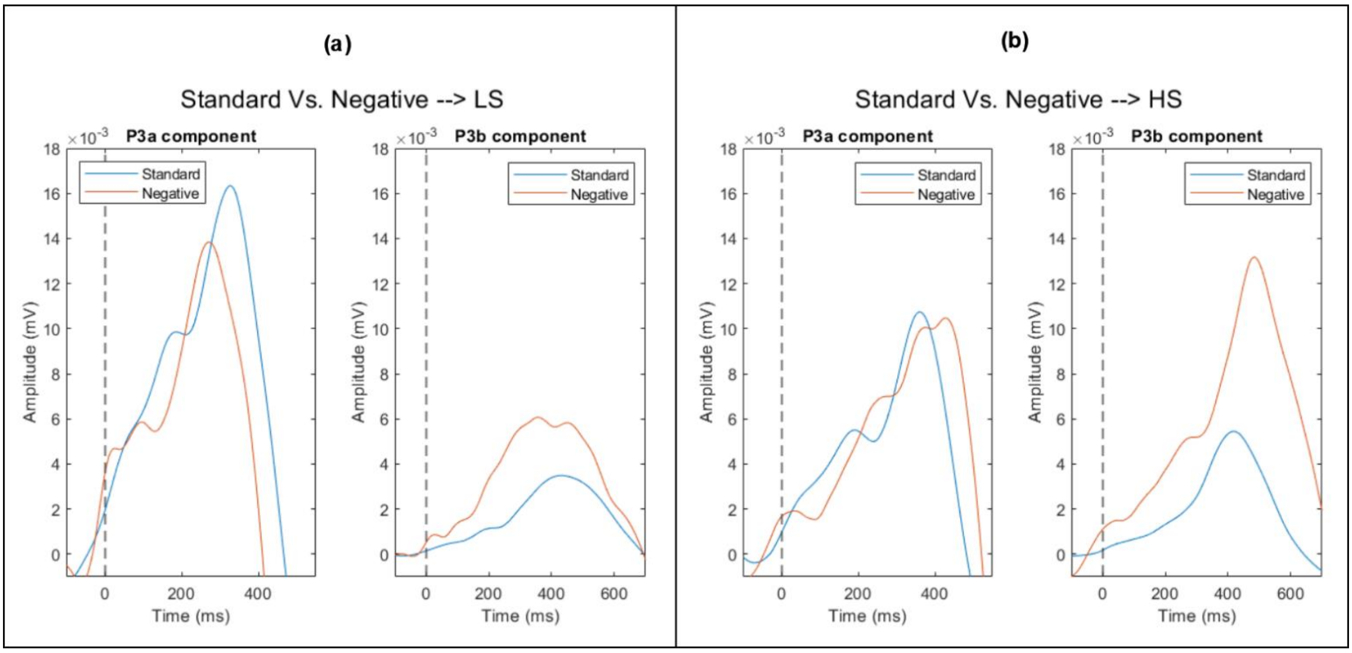

Figure 5. The comparison of P300 subcomponents between standard and negative mood descriptor for LS(a) and HS(b) groups.

Table 2. The mean value (S.D.) and statistical comparison between the mood descriptors for HS and LS groups. The significant changes are highlighted in bold ($P < 0.05$).

Participants' group	Component	Features	Normal	Positive	Negative	Neutral	Normal vs. Negative		Normal vs. Positive		Normal vs. Neutral		Neutral vs. Positive		Neutral vs. Negative		Positive vs. Negative	
							t-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value
HS	P3a	Amplitude (mV)	0.0088 (0.0048)	0.0123 (0.009)	0.0106 (0.0078)	0.0108 (0.0078)	0.964	0.3474	1.733	0.1001	1.164	0.2596	0.645	0.5266	-0.147	0.8842	-0.851	0.4056
		Latency (ms)	314 (70)	295 (73)	283 (67)	287 (74)	-1.501	0.1505	-0.816	0.4247	-1.277	0.2178	0.358	0.7240	-0.114	0.9099	-0.488	0.6311
	P3b	Amplitude (mV)	0.0062 (0.0036)	0.0088 (0.0041)	0.0109 (0.006)	0.0069 (0.0052)	**3.647 ***	**0.0018 ***	**2.401 ***	**0.0273 ***	0.53	0.5964	1.200	0.2455	**2.419 ***	**0.0264 ***	1.739	0.0989
		Latency (ms)	423 (82)	470 (100)	487 (69)	402 (89)	**3.334 ***	**0.0037 ***	1.586	0.1301	-0.959	0.3501	1.958,	0.0658	**3.654 ***	**0.0018 ***	0.684	0.5022
LS	P3a	Amplitude (mV)	0.0097 (0.0072)	0.0153 (0.0143)	0.0129 (0.0159)	0.0103 (0.0085)	1.024	0.3324	1.000	0.3431	0.140	0.8914	1.210	0.2571	0.406	0.6936	-0.377	0.7147
		Latency (ms)	300 (74)	296 (69)	276 (73)	285 (61)	-1.549	0.1557	-0.130	0.8992	-0.551	0.5947	0.406	0.6937	-0.272	0.7911	-0.696	0.5035
	P3b	Amplitude (mV)	0.0042 (0.0046)	0.0056 (0.0031)	0.004 (0.003)	0.0049 (0.0034)	-0.112	0.9130	0.837	0.4242	0.435	0.6737	0.516	0.6177	-0.582	0.5745	-1.649	0.1334
		Latency (ms)	456 (47)	450 (116)	424 (83)	441 (101)	-0.887	0.3980	-0.179	0.8616	-0.387	0.7077	0.143	0.8892	-0.564	0.5860	-0.616	0.5531

*P<0.05

Table 3. Statistical results for comparing HS and LS groups during different mood descriptors. The significant changes are highlighted in bold ($P < 0.05$).

Participants' group	Components	Features	Normal		Neutral		Negative		Positive	
			t-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value
HS vs. LS	P3a	Amplitude	-0.422	0.6758	0.154	0.8782	-0.528	0.6016	-0.703	0.4877
		Latency	0.502	0.6193	0.075	0.9407	0.271	0.7882	-0.023	0.9814
	P3b	Amplitude	1.313	0.2002	1.055	0.3006	**3.401 ***	**0.0021 ***	**2.122 ***	**0.0431 ***
		Latency	-1.161	0.2555	-1.077	0.2908	**2.161 ***	**0.0397 ***	0.473	0.6396

* $P < 0.05$

In addition, four-way tensor and SSA are used to obtain the visual comparison of P300 subcomponents between HS and LS groups. Figure 6 illustrates the visual comparison between two groups of schizotypy in standard, positive, and negative mood descriptors.

3.2 Classification

In this study, the EEGs from twenty-nine participants (19 HS and 10 LS) were used to assess the classification performance using the LOO-CV methodology. So, the model was trained on 28 participants while one participant was used as a test set. The set of features has been extracted, resulting in a total of 528, including P3a and P3b features (([P3a + P3b] × [amplitude + latency] × 4 mood descriptors), and whole P300 component features for all electrodes (64 electrodes × [amplitude + latency] × 4 mood descriptors). MI has been used for feature selection after feature ranking using *t*-test. Manual grid search has been used to select the optimal feature space. Table 4 demonstrates the classification performance of the proposed method.

The results of classification performance indicate the high effectiveness of ERP features for schizotypy assessments. Evidently, most of the participants (27 out of 29) are diagnosed correctly using the polynomial-SVM classifier.

Table 4. The classification performance using different classifiers.

Classifier type	Accuracy	Specificity	Sensitivity	F1-score
DT	82.75	80	84.21	0.86
LDA	89.65	90	89.47	0.91
Linear-SVM	93.1	80	100	0.95
Polynomial-SVM	93.1	90	94.73	0.94

4. Discussion

People with psychosis without mood disturbance, e.g., schizophrenia spectrum disorder, have experiences that include hearing voices, belief in supernatural activities and a belief that others are trying to harm them. Schizotypy is more common in families of people with schizophrenia (10%) than those with depression (1%), making schizotypy a risk to experience psychosis [54]. Diagnosis of schizotypy potentially provides early identification of mental disorders. On the other hand, any delay in diagnosis and treatment of psychosis-like signs contributes to poorer outcomes in psychosis [55]. Technological advances in signal processing exploit the multi-modal brain responses to accurately classify the people with schizotypy, which is a sub-clinical personality trait akin to psychosis [37]. In this study, tensor factorization, a state-of-the-art method, has been used for accurate detection of P300 subcomponents, namely P3a and P3b. To the best of our knowledge, this study is the first attempt to classify HS and LS participants using P300 subcomponents elicited during a novel social cognition auditory oddball task depicting family stress.

As hypothesised, the P3b amplitude during deviant mood-congruent target words that followed criticism and praise was higher than the standard target word that followed these comments. This difference in P3b amplitude was present in the HS group, not the LS group, whereas, the P3a amplitude did not change. This finding suggests that in contrast to P3b, P3a is an inadvertent reaction of the brain to task-irrelevant stimulus events [17, 20]. Our study also shows for the first time increased P3b amplitude to the oddball in the HS group in this social cognition oddball task depicting family stress. The findings indicate that the P3b amplitude during deviant mood-congruent words following criticism and praise is higher in the HS group than the LS group. The higher P3b amplitude and longer P3b latency for negative words that follow criticism than neutral words that follow praise in the HS group further emphasise the salience of negative words

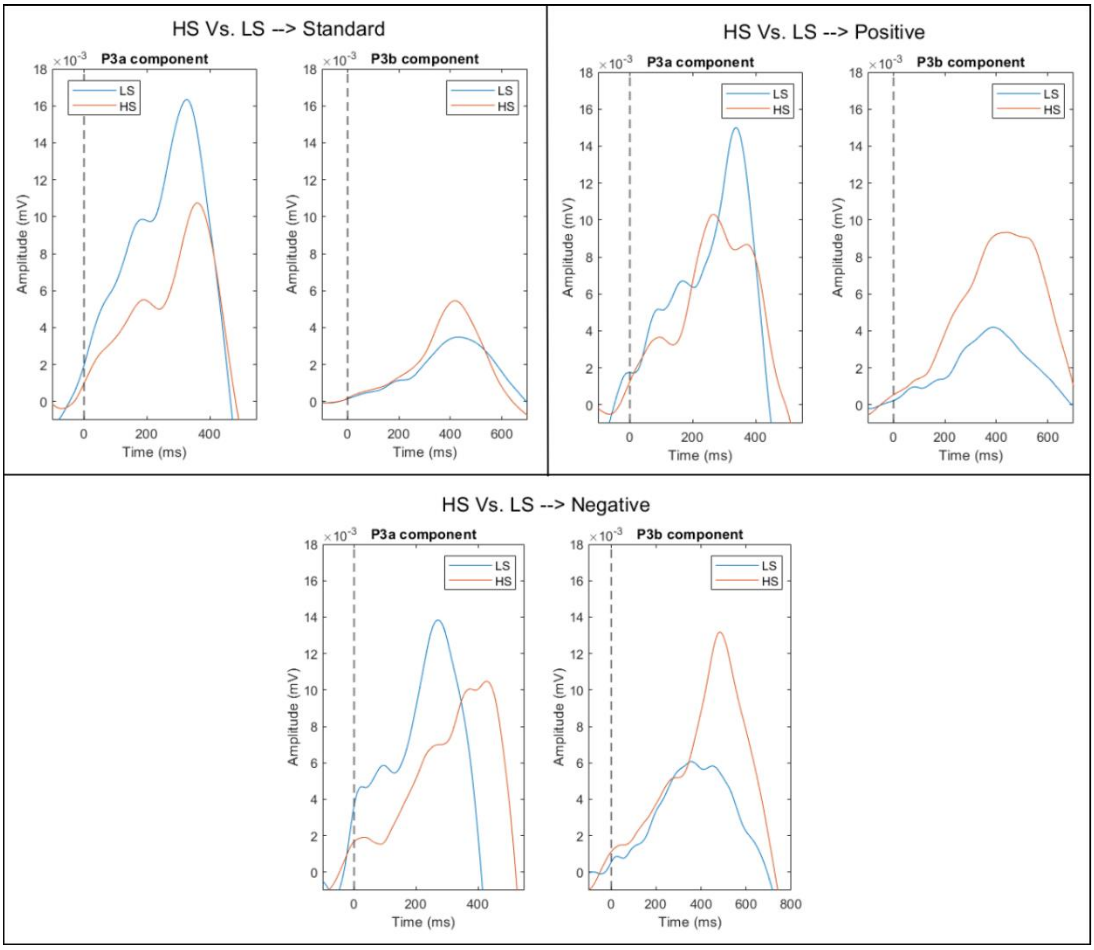

Figure 6. The comparison between P300 subcomponents for HS and LS in standard, positive, and negative mood descriptors.

following criticism in the HS group. These findings are consistent with the results of some previous studies of increased P300 amplitude in those at risk for psychosis or in relation to HS [29, 34] and support our third hypothesis of increased P3b amplitude during deviant target words that follow criticism and praise in the HS group. High P3b amplitude suggests selective and sustained attention to the target stimulus; it relates to the performance of working memory and sustained attention in schizophrenia patients [56]. Abnormally high P300 amplitude in individuals at the risk of psychosis who also have autism is a risk factor for conversion to psychosis [34]. These findings suggest that people with HS have increased sustained attention to negative words that follow criticism and positive words that follow praise. The criticism and praise depict high expressed emotion (EE) and comments made by a close relative [7, 57]. HS is associated with greater relevance to oneself of the criticisms and less relevance of the praises that were used in this novel oddball task [7]. Individuals with HS also encounter high expressed emotion due to hostility more often than individuals with LS [6]. The increased P3b amplitude during negative and positive words that follow criticism and praise, respectively, and the longer P3b latency to negative words that follow criticism suggest that individuals with HS are primed by such comments possibly due to encountering these styles of communication in their family. The findings further reinforce the assumption that high EE is a risk factor for vulnerability for psychosis and not necessarily the consequence of the burden of illness [58]. High EE is a significant risk factor for schizophrenia, since there is 50% risk that people with schizophrenia who experience high EE will relapse a year later, i.e. deteriorate after a period of symptomatic relief [59]. On the other hand, a good relationship (warmth) reduces the risk of relapse by 58% after six months in people with first episode psychosis [60]. Diminished emotion regulation and more effort needed to glean the emotional words may underlie the higher P3b amplitude and sustained attention to these emotional words. Lower P300 amplitude is found during negative words that follow the emotion regulation strategy where one increases the unpleasant emotion felt by seeing an unpleasant image in healthy individuals [61]. The findings in that study suggested that increasing the intensity of negative feelings to an unpleasant image may limit the cognitive resources to a subsequent negative word and so result in lower P300 amplitude to the negative word.

Furthermore, shorter P300 latencies imply higher speed of processing and classification and more efficient attentional resources [62]. P300 latency indicates the time used between perception and reaction and also some monitoring process [63]. Our results show that the latency of P3b response to neutral target words following criticism is shorter than that for negative target words following neutral comments in the HS group. This suggests lower speed of processing for negative than neutral words. In this study, greater P3b latency to the deviant negative target words following criticism in the HS than LS group, may suggest delay in processing the meaning of the negative words. Hearing the criticism may hinder or delay the ability to attend to negative words.

Finally, the machine learning results show that the ERP components may be a valuable brain biomarker for schizotypy assessment. From Table 4, our proposed method can classify most of the participants using some simple classifiers.

The small dataset size is the major limitation of this study due to the loss of a large number of individuals who were not in the schizotypy score range. For more reliability of the proposed method, future studies should recruit a larger number of subclinical participants. In this data collection, we only distinguished between trials based on the target word. Future studies should also put the standard trials into three categories based on whether the comment that preceded the target word is a criticism, praise or neutral comment to know what type of comment preceded the target word in the standard trials.

5. Conclusion

This study is the first attempt to detect P3a and P3b components for schizotypy during a novel auditory oddball task using CP decomposition technique. We aimed to determine whether P3a and P3b amplitudes to deviant mood-congruent target words following criticism and praise differ between people with HS and LS. These findings indicate that the P3b amplitude during deviant mood-congruent words following criticism and praise differ between the two groups. The significant group difference was observed for the P3b latency during deviant mood-congruent words following criticism. Also, we attempted to use machine learning algorithms to distinguish between two groups of schizotypy and succeed in producing a high level of accuracy in classification of HS and LS groups based on the P3a and P3b ERPs. Taken together, these results prove not only the power of tensor factorization in ERP detection but also the importance of P300 subcomponents in the assessment of schizotypy. Besides, we demonstrated that the family communication may affect social cognition in people with schizotypy. So, there is a need to offer more support and psychoeducation to families with HS about the nature of schizotypy and its association with communication deviance. The purpose is to understand how a carer's family communication affects brain activity (using audio and visual tasks that mimic the family communication) in people with schizotypy. Thus, we understand how the family communication contributes to the neurophysiology underlying psychosis-like experiences at a non-clinical level.

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