Electroencephalogram-derived Involvement Indexes in Sensory Processing Sensitivity

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Erica Iammarino, *Student Member, IEEE,* Ilaria Marcantoni, *Member, IEEE*, and Laura Burattini, *Member, IEEE*

***Abstract*— Sensory processing sensitivity (SPS) is a temperament trait observed in highly sensitive persons (HSPs) characterized by heightened responsiveness to environmental and social stimuli. Up to now, this condition has been assessed through the HSP scale, but the neurophysiological correlates of SPS have started to be investigated by the electroencephalogram (EEG). In this context, this study aims to investigate the role of EEG-derived involvement indexes as physiological markers for characterizing and possibly identifying HSPs, contributing to existing evidence of SPS by resting-state EEG. To do so, resting-state EEG data published by Dimulescu et al. were analyzed in EEGLAB. After preprocessing involving 0.5-80 Hz band-pass filtering, average re-referencing, and artifact removal via independent component analysis, EEG rhythms were extracted, and 37 involvement indexes were computed as the ratio of powers and/or power summations of two or more EEG rhythms. Comparisons between HSPs and non-HSPs were performed per brain rhythm using the Wilcoxon rank-sum test, setting statistical significance *p* to 0.05, while group differences in involvement indexes were evaluated by analysis of variance (ANOVA). A more pronounced EEG brain rhythm activity in HSPs was observed, except for the alpha rhythm that resulted to be more pronounced in the non-HSP group. As for involvement indexes, 13 indexes resulted to be statistical significant in distinguishing HSPs from non-HSPs. Our results suggest that: (1) HSPs and non-HSPs exhibit different spectral patterns in resting-state EEG; (2) EEG-derived involvement indexes, especially those defined considering both low-frequency and high-frequency oscillations, may be useful to characterize SPS.**

***Clinical Relevance*— The present study provides electroencephalographic evidence to identify highly sensitive persons, contributing to create an objective way to recognize this temperament trait.**

I. Introduction

Sensitivity is an intrinsic aspect of human experience, but the extent to which individuals perceive and react to the external world varies significantly. Some people exhibit heightened sensitivity in their daily lives, becoming deeply affected by other people's emotions and behaviors, as well as being attentive to the finest details. These individuals tend to respond intensely to stimuli that others may scarcely even notice. This heightened responsiveness to environmental and social stimuli is recognized as a distinct temperament trait, known as sensory processing sensitivity (SPS) [1-3]. Since its introduction in the 1990s, SPS has been acknowledged as an important factor affecting personality, behavior and well-being. Indeed, those with high SPS, also known as highly sensitive persons (HSPs), exhibit deeper cognitive processing, stronger emotional reactivity, enhanced awareness, and greater empathy and self-reflection [4]. Up to now, high sensitivity has been assessed through the HSP scale (HSPS) introduced by Aron and Aron in 1997 [5]. Using this scale, it has been estimated that approximately 15-20% of individuals score high enough to be classified as HSPs [3]. The HSPS consists of a 27-item questionnaire, where the subject is asked to rate each item with a score from 1 ("not at all") to 7 ("extremely") representing the level of agreement with it. Subsequently, studies have investigated the psychometric properties of the HSPS and have demonstrated that SPS should not be confused with introversion, neuroticism, or neurological disorders with common symptoms, such as schizophrenia, autism spectrum disorder and post-traumatic stress disorder [2,6,7]. Moreover, Smolewska et al. introduced a three-component structure of the HSPS consisting of: (1) aesthetic sensitivity, reflecting aesthetic awareness, (2) low sensory threshold, indicating unpleasant sensory arousal in response to external stimuli, and (3) ease of excitation, referring to the susceptibility to being overwhelmed by stimuli [7].

Given its association with deep cognitive processing and heightened emotional reactivity, neurophysiological correlates of SPS started to be investigated to assess whether there are distinct patterns of brain activity in HSPs. Functional magnetic resonance imaging (fMRI) studies have shown a positive correlation between SPS and neural activations in brain regions involved in attention, action planning, awareness, integration of sensory information and empathy, as well as in brain areas involved in high-order visual processing. Moreover, the studies by Acevedo and colleagues found differences in resting-state functional connectivity, especially between hippocampus and precuneus (implicated in episodic memory), and between hippocampus and insula (implicated in cognitive processing) [1,2,8].

In addition to fMRI, brain activity can also be investigated via electroencephalogram (EEG), which is the direct and non-invasive recording of brain electrical activity at the scalp level. The EEG can be used to assess an individual's mental state and level of involvement by analyzing specific frequency bands – also known as brain rhythms – distributed along the EEG frequency content: delta, theta, alpha, beta, and gamma. As noted by Wang et al. [9], the spectral powers of single brain rhythms may not be all-inclusive markers to consistently

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E. Iammarino is with the Department of Information Engineering, Università Politecnica delle Marche, Ancona, Italy (corresponding author, phone: 071 2204465; e-mail: e.iammarino@pm.univpm.it).

I. Marcantoni and L. Burattini are with the Department of Information Engineering, Università Politecnica delle Marche, Ancona, Italy (e-mail: i.marcantoni@staff.univpm.it; l.burattini@univpm.it).

assess mental involvement. Instead, combining the spectral powers of multiple brain rhythms may be preferable. Indeed, a more comprehensive characterization of the level of mental involvement can be obtained by computing indexes of involvement, defined as the ratio of the spectral powers of two or more brain rhythms. Marcantoni et al. [10] systematically reported 37 EEG-derived ratio indexes used in the literature to assess human mental involvement. These 37 indexes have been already studied in mental disorders like schizophrenia [11], and for evaluating cognitive impairments that may occur in neurological disorders like epilepsy [12]; however, they do not yet represent an established procedure and their potential to characterize SPS is still unexplored. Indeed, despite the growing interest in using EEG to investigate individual differences in cognitive and emotional processing, research on the neural correlates of SPS using EEG remains limited. To date, only three studies have examined this relationship and none of them has used EEG-derived involvement indexes. Indeed, these studies focused only on the analysis of the spectral power of various EEG frequency bands in resting-state condition [13-15].

In this context, the present study aims to evaluate the role of EEG-derived involvement indexes as physiological markers for characterizing and possibly identifying HSPs, thereby contributing to existing evidence of SPS by resting-state EEG.

II. Materials and Methods

A. Study Population

The population analyzed in the present study comes from the dataset published by Dimulescu et al. in 2019 on OSF (https://osf.io/pgtu6/?view_onl, accessed on 1st December 2024) [15]. The dataset includes EEG data recorded using the ActiView software from 20 participants who were instructed to keep their eyes closed and relax during the acquisition. EEG data were recorded for 15 minutes using 32 Ag-AgCl BioSemi Active electrodes placed according to the 10-20 system. The sampling frequency was 2048 Hz, while the electrode impedance was kept below 2500 Ω. The study population consisted of 13 females and 7 males, with age ranging from 19 to 55 years. All participants filled in the 27-item HSPS and, according to the HSP scores, they were classified in HSPs and non HSPs (non-HSPs) by the dataset authors [15].

B. Preprocessing of Electroencephalographic Data

EEG preprocessing was performed in MATLAB R2022b using EEGLAB. First of all, EEG data were down sampled to 500 Hz and re-referenced to the average of all electrodes. Then, a finite impulse response filter was applied, with lower and upper cutoff frequencies of 0.5 and 80 Hz, respectively. After that, powerline noise at 50 Hz was removed using *CleanLine* plug-in, while artifact removal by independent component analysis (ICA) was performed using *ICLabel* plug-in [16]. Specifically, independent components obtained by ICA decomposition were automatically classified by a pre-trained classifier implemented within the plug-in. This classifier assigns each component the probability of belonging to seven possible classes: "brain", "muscle", "eye", "heart", describing biological sources, "line noise", and "channel noise", describing non-biological sources, and "other". Components with a probability of being "brain" lower than 5% or with a probability of at least another class being greater than 90% were removed from the EEG signal. Preprocessed EEG signals were then windowed. Specifically, 1-minute EEG windows were recursively extracted every 2 s until the end of the signal was reached. Then, to detect any bad channels within each 1-minute EEG window, further windowing was performed by recursively extracting consecutive 3-s windows every second. Bad channels were identified according to a metric based on the standard deviation of the EEG signal computed in each of the 3-s windows. More in detail, if four times the standard deviation of the EEG signal exceeded 100 μV in at least 20% of the 3-s EEG windows, the corresponding EEG channel was rejected from the 1-minute EEG window considered.

C. Extraction of Brain Rhythms and Involvement Indexes

For each 1-minute EEG window and accepted channel, the following six frequency bands were considered for extraction of brain rhythms: 0.5–4 Hz for delta rhythm (δ), 4–8 Hz for theta rhythm (θ), 8–12 Hz for alpha rhythm (α), 12–15 Hz for somatosensory rhythm (SMR), 13–30 Hz for beta rhythm (β), and 30–70 Hz for gamma rhythm (γ). A 6th-order bidirectional Butterworth filter was implemented to extract such rhythms. After that, for each brain rhythm extracted, the power spectral density was estimated by Welch's overlapped segment averaging method and characterized by computing the area under the curve, as quantification of the spectral power energy. Based on these spectral features, 37 involvement indexes were derived. These indexes are defined as the ratio of the spectral power of two or more EEG rhythms, and their mathematical definition is detailed in Table I [10]. The SMR was extracted

TABLE I. Mathematical Formulas of the Involvement Indexes

Index	Formula	Index	Formula	Index	Formula
I_1	$\frac{\beta}{\alpha}$	I_{14}	$\frac{\delta+\theta+\alpha}{\beta}$	I_{27}	$\frac{\alpha}{\theta+\alpha+\beta}$
I_2	$\frac{\beta}{\theta+\alpha}$	I_{15}	$\frac{\delta+\theta}{\alpha}$	I_{28}	$\frac{\beta}{\theta+\gamma}$
I_3	$\frac{\beta}{\theta}$	I_{16}	$\frac{\delta+\theta}{\alpha+\beta}$	I_{29}	$\frac{\beta+\gamma}{\delta}$
I_4	$\frac{\theta}{\alpha}$	I_{17}	$\frac{\delta}{\alpha}$	I_{30}	$\frac{\alpha+\beta}{\gamma}$
I_5	$\frac{\theta}{\delta}$	I_{18}	$\frac{\delta}{\beta}$	I_{31}	$\frac{\alpha+\gamma}{\delta+\theta}$
I_6	$\frac{SMR}{\theta}$	I_{19}	$\frac{\theta}{\gamma}$	I_{32}	$\frac{\theta+\alpha}{\delta}$
I_7	$\frac{SMR}{\beta}$	I_{20}	$\frac{\alpha}{\gamma}$	I_{33}	$\frac{\theta+\beta}{\alpha+\gamma}$
I_8	$\frac{\alpha+\beta}{\delta}$	I_{21}	$\frac{SMR+\beta}{\theta}$	I_{34}	$\frac{\beta+\gamma}{\delta+\theta}$
I_9	$\frac{\theta+\alpha}{\alpha+\beta}$	I_{22}	$\frac{\theta+\alpha}{\beta+\gamma}$	I_{35}	$\frac{\delta+\alpha}{\theta+\gamma}$
I_{10}	$\frac{\theta}{\alpha+\beta}$	I_{23}	$\frac{\alpha+\beta}{\theta+\alpha}$	I_{36}	$\frac{\theta+\alpha}{\delta+\beta+\gamma}$
I_{11}	$\frac{\theta+\alpha}{\gamma}$	I_{24}	$\frac{\alpha}{\beta+\gamma}$	I_{37}	$\frac{\alpha+\beta}{\delta+\theta+\gamma}$
I_{12}	$\frac{\theta+\beta}{\alpha}$	I_{25}	$\frac{\delta+\theta+\alpha}{\beta+\gamma}$		
I_{13}	$\frac{\delta+\theta}{\beta}$	I_{26}	$\frac{\alpha}{\delta+\theta+\alpha}$		

for the computation of the involvement indexes but was not included among the brain rhythms in the following analysis since its frequency band is almost entirely comprised in the beta rhythm.

D. Statistics

For each EEG channel, brain rhythms and involvement indexes were averaged over the 1-minute EEG windows by computing the median. Then, EEG channels were grouped in five brain regions, as shown in Fig. 1. The brain regions considered were the frontal, the central, the temporal, the parietal and the occipital. Specifically, EEG rhythms and EEG-derived involvement indexes computed on EEG signals of the same brain region were averaged (mean) distinguishing left and right sides of each region.

The median spectral power of each EEG rhythm was computed on the HSP group and on the non-HSP one, and the difference between the two median powers was also evaluated. Similarly, the median value of each involvement index was computed on the HSP group and on the non-HSP one, and the difference between the two median values was evaluated for each brain region and EEG channel.

Comparisons between HSPs and non-HSPs were performed for each brain rhythm using the Wilcoxon rank-sum test, setting statistical significance p to 0.05. The analysis was conducted at both brain-region level (*i.e.*, region by region) and channel level (*i.e.*, channel by channel). To evaluate group differences in EEG-derived involvement indexes, a three-way analysis of variance (ANOVA) was conducted, with subject group (*i.e.*, HSP or non-HSP), EEG channel and involvement index as grouping variables, and involvement index values as the dependent variable. The model tested for the main effects of subject group, EEG channel and involvement index, as well as the possible two-way interactions among them. To further investigate group-related effects, if a significant two-way interaction involving the subject group was observed, a two-way ANOVA was performed within each level of the third grouping variable, *i.e.,* across involvement indexes for each EEG channel or across EEG channels for each involvement index, depending on the interaction identified.

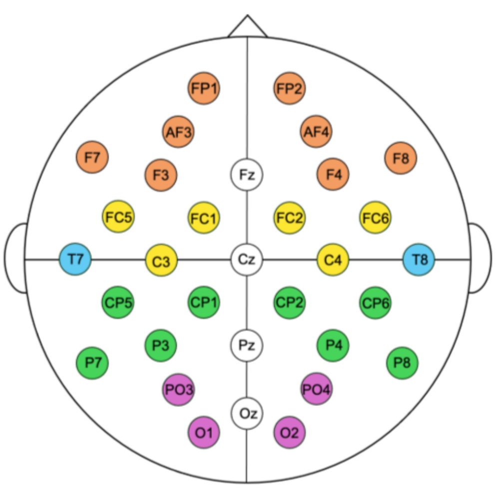

Figure 1. Grouping of EEG channels by brain region. Frontal channels are represented in orange, central channels in yellow, temporal channels in blue, parietal channels in green and occipital channels in purple. White channels were not considered. Following neurological convention, the left hemisphere is displayed on the left side.

III. Results

When comparing brain rhythms between HSPs and non-HSPs at the brain region level, significant differences were observed in the frontal left and central left regions. Specifically, spectral powers of θ and γ rhythms were statistically different in the frontal left region, while spectral powers of β and γ rhythms were statistically different in the central left region. Fig. 2 presents topographic maps displaying spectral powers of brain rhythms, and p-values obtained comparing spectral powers of HSPs and non-HSPs channel by channel. More specifically, the first row shows the median spectral powers computed over the HSP group, the second row shows the median spectral powers computed over the non-HSP group, the third row shows the difference in median spectral power between the two groups, and the last row displays the p-values, indicating the channels where spectral power differences reached statistical significance, which are: P7 for δ, θ, β and γ rhythms; F7 for θ and β rhythms; FC5 for θ rhythm; C3 for β and γ rhythms; and O1 for γ rhythm.

Differences between the median value of each involvement index computed over the HSP group and over the non-HSP one in each brain region are shown in Fig. 3. Specifically, panel A shows the differences observed in left brain regions while panel B shows the differences observed in right brain regions. These group differences computed for each EEG channel are displayed in Fig. 4.

The 3-way ANOVA revealed significant main effects of channel ($F(31, 22428) = 21.02$; $p < 0.001$) and involvement index ($F(36, 22428) = 420.61$; $p < 0.001$), while the main effect of the subject group was not significant ($F(1, 22428) = 0.34$; $p = 0.50$). Moreover, there were significant two-way interactions between channel and subject group, $F(31, 22428) = 5.23$, $p < 0.001$; involvement index and subject group, $F(36, 22428) = 1.47$, $p < 0.001$; and channel and involvement index, $F(1116, 22428) = 3.86$, $p < 0.001$. Based on these outcomes, 2-way ANOVA was performed for each involvement index, considering subject group and EEG channel as grouping variables, as well as for each EEG channel, considering subject group and involvement index as grouping variables. When considering each involvement index, ANOVA revealed a significant main effect of subject group for indexes I_5, I_6, I_7, I_8, I_{21}, I_{32} I_{36} with $p < 0.001$, for indexes I_{19}, I_{31}, I_{37} with $p < 0.01$, and for indexes I_{22}, I_{24}, I_{28} with $p < 0.05$, while no significant interaction between subject group and channel was found. Eventually, when considering each EEG channel, ANOVA revealed a significant main effect of subject group for channels Oz, O2, P8 with $p < 0.001$, and for channels T7, CP1, Pz, CP2, FC6, AF4 with $p < 0.05$, as well as a significant interaction between subject group and involvement index for channels Oz, O2, and P8. Focusing on these channels, pairwise comparisons pointed out that indexes I_{11}, I_{20}, and I_{30} were statistically different between HSPs and non-HSPs.

IV. Discussion

The aim of this study was to assess the role of EEG-derived involvement indexes in characterizing and identifying HSPs, thereby contributing to the body of evidence on the

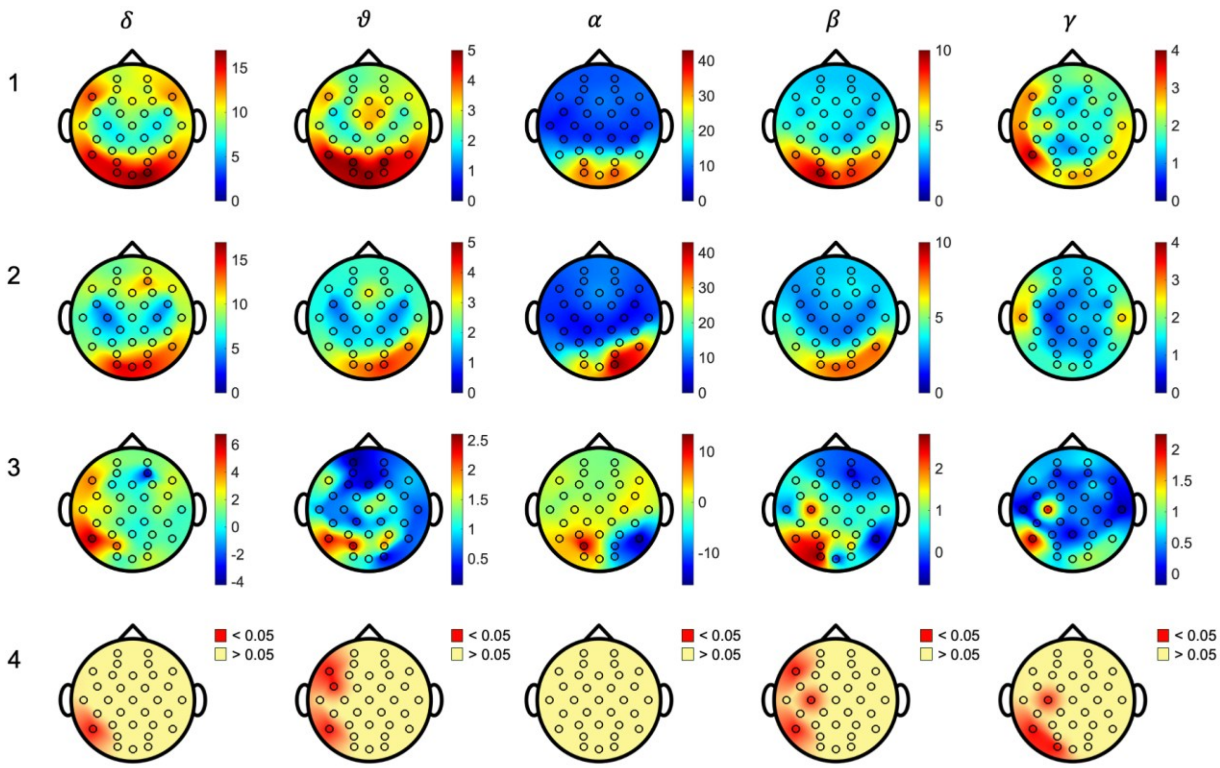

Figure 2. Topographic maps of brain rhythm spectral powers (expressed in $\mu V^2/Hz$) and *p*-values. First row shows median spectral power on the HSP group; second row shows median spectral power on the non-HSP group; third row shows the group differences in median spectral power; fourth row shows the p-values obtained comparing HSPs and non-HSPs spectral powers.

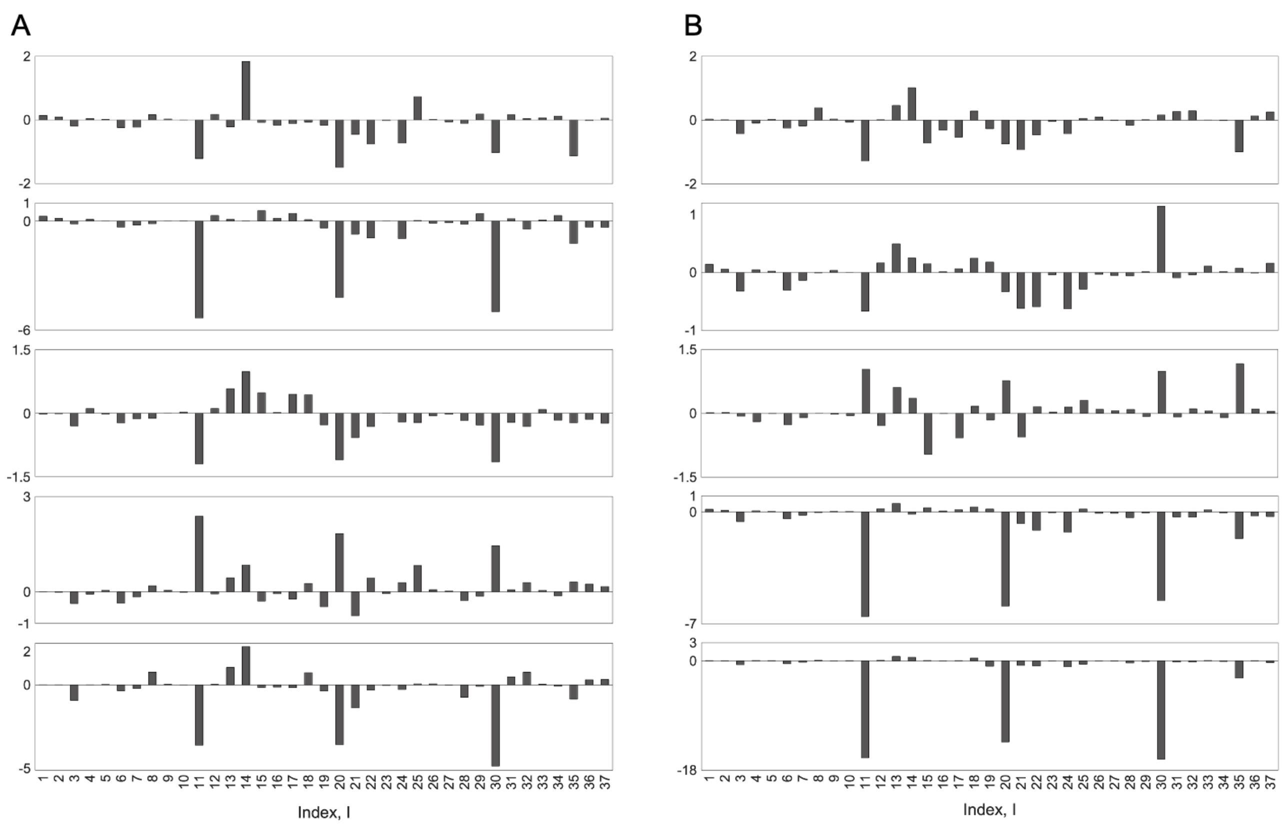

Figure 3. Bar plots illustrating group differences in EEG-derived involvement indexes per brain region. Panel A shows differences in left brain regions and panel B in right brain regions. From top to bottom, brain regions are reported as frontal, central, temporal, parietal, and occipital (different value ranges for y-axes were used for a better visualization).

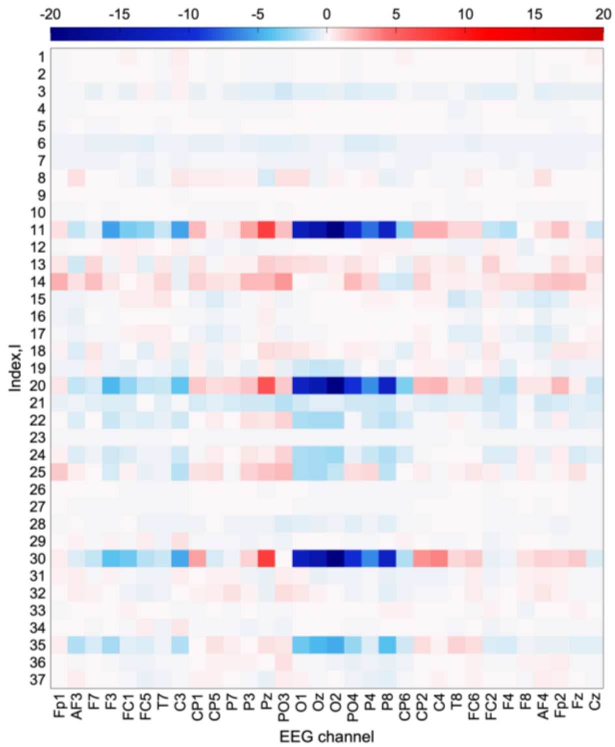

Figure 4. Heatmap showing group differences in EEG-derived involvement indexes per channel. Each cell represents the difference between the median value of a specific index (y-axis) computed on a specific channel (x-axis) in the HSP group and in the non-HSP group. Toward-red colors indicate higher feature values in HSPs, toward-blue colors indicate higher feature values in non-HSPs.

neural correlates of SPS. To achieve this, the dataset of Dimulescu et al. was selected. The choice was prompted by the fact that the population was already divided into HSPs and non-HSPs based on their HSPS score, and that their EEG was acquired in resting conditions. EEG data were processed using EEGLAB, and the recently introduced *ICLabel* plug-in was exploited to reject independent components that were automatically classified as artifact. This methodology was applied in order to provide a systematic, objective and reproducible procedure that can be also extended to larger databases. In addition, EEG windowing was performed to isolate possible local artifacts and reject bad channels, promoting more reliable results.

The analysis of brain rhythms and EEG-derived involvement indexes performed in this study provides promising first insights into the neural correlates of SPS, suggesting that this line of research should be pursued. Focusing on brain rhythms (Fig. 2), results showed more pronounced EEG activity in the HSP group across all frequency bands but the alpha rhythm that, especially in the occipital brain region, resulted to be more pronounced in the non-HSP group than in the HSP one. These findings are in accordance with previous studies on HSPs [14,15] and support the hypothesis that SPS is characterized by enhanced cognitive processing, which is reflected in increased brain oscillations in beta and gamma frequency bands and in a decreased alpha power. Moreover, the observed increase in resting-state delta and theta activity have been associated to emotional processes, inhibitory control and attention to internal processing, meaning that HSPs may also be better at shifting their attentional focus from possible external distractors to their own internal state [17-19]. This implies that, despite their heightened sensitivity to external stimuli, HSPs may have a more effective attention regulation mechanism under certain circumstances, which enables them to better handle sensory overload.

Focusing on involvement indexes, median values were almost always different between HSPs and non-HSPs, as shown in Fig. 3 and Fig. 4. However, the 2-way ANOVA revealed that 13 indexes significantly distinguished between the two groups. According to the mathematical formulas reported in Table I, index I_5 reflects the relationship between theta and delta rhythms that, as previously discussed, are associated to internal and emotional processing and resulted to be enhanced in SPS; index I_7 captures the interplay between SMR and beta rhythm, both linked with introverted concentration, active attention and conscious thinking [20]; indexes I_6, I_8, I_{13}, I_{14}, I_{19}, I_{21} and I_{28} relate high-frequency rhythms (alpha, beta and/or gamma, associated with high cognitive processing) to low-frequency rhythms (delta and/or theta, linked to relaxation and internal processing) or vice versa, suggesting that they both contribute to defining distinct neurological patterns in SPS. Similar observation can be done considering indexes I_{31}, I_{32}, I_{35}, I_{36}, which are defined as combinations of high-frequency and low-frequency rhythms at both numerator and denominator. The absence of significance in other indexes may be due to the limited sample size, as well as individual variability. Lastly, indexes I_{11}, I_{20}, and I_{30}, which resulted to be significant in channels Oz, O2 and P8, have alpha at the nominator and gamma at the denominator in their definition, suggesting that these two rhythms may play a fundamental role in characterizing SPS and defining distinct spectral patterns in HSPs.

Regarding the brain regions considered, spectral powers of EEG rhythms were statistically different between HSPs and non-HSPs in frontal and central brain regions. This is in accordance with the known involvement of these regions in cognitive control, attention, emotional regulation, and sensorimotor integration. When comparing involvement indexes, statistical significance was reached also in parietal and occipital brain regions, which are involved in sensory integration and visual processing. Thus, the observed differences in these brain regions may reflect the heightened sensory processing, emotional reactivity, and visual attention characteristic of HSPs, which often involve increased focus and deeper processing of sensory stimuli, suggesting also that the brain activity associated with SPS cannot be confined to a single brain region. Previous studies have found significant differences in temporal brain regions [13,14]. However, the lack of significant differences in such regions in our study may be attributed to the fact that EEG was recorded using a single channel in such areas. Thus, a higher spatial resolution, involving multiple channels, is necessary to further explore the EEG activity in temporal brain regions. It should also be noted that, due to the lack of standardization, electrode grouping may vary depending on the methodological choices of each study, and this should be taken into account when interpreting and comparing findings related to brain regions. Moreover, future studies should deepen and possibly confirm the lateralization that can be seen in Fig. 2.

Some limitations of the present study should be noted. First of all, the study population includes only 10 subjects per group, not allowing for robust statistical generalization of the obtained outcomes, which have to be intended as preliminary. Furthermore, there was only one male in the HSP group. Although gender may not be a significant confounding factor in SPS, further studies, possibly involving larger groups with similar clinical profiles, are needed.

Therefore, this pilot study confirms previous research on resting-state EEG spectral patterns and offers first insights into the potential value and use of EEG-derived involvement indexes for further research on SPS. Future studies should perform an analogous analysis of the involvement indexes on larger databases, possibly validating the current findings and leveraging them as a reliable term of comparison.

V. Conclusion

This study suggests that: HSPs and non-HSPs exhibit different spectral patterns in resting-state EEG, especially within theta, beta and gamma frequency bands; EEG-derived involvement indexes, especially those defined considering both low- and high-frequency oscillations, may be useful to characterize SPS; and differences between HSPs and non-HSPs seem not to be confined to a single brain region, even if frontal and central brain regions resulted the most effective in pointing out such differences.

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