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Functional Connectivity Analysis of Prejudice Among Colombian Armed Conflict Former Actors

Análisis de conectividad funcional del prejuicio entre antiguos actores del conflicto armado colombiano

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Abstract.
Despite institutional efforts, reconciliation among former actors of the Colombian armed conflict has yet to be achieved, with prejudice being one direct driver of this drawback. We present an EEG-based functional connectivity study applied to four groups of former actors who completed an Implicit Association Test designed to measure prejudice toward victims or combatants. We analyzed seven measures of functional connectivity calculated in six different frequency bands and two experimental conditions. In the behavioral task, we found more prejudice toward victims from the same victims and more prejudice of civilians toward combatants. For the connectivity measures, we found differences in theta band among the victims' and ex-paramilitaries' groups concerning the civilians' and ex-guerrillas' groups, and differences in the beta2 band among the victims' and ex-guerrillas' groups concerning the ex-paramilitaries' group. The results help us design more effective socio-cognitive interventions to reduce prejudice.

Resumen.
A pesar de los esfuerzos institucionales, aún no se ha logrado la reconciliación entre antiguos actores del conflicto armado colombiano, debido en parte al prejuicio que todavía persiste. Presentamos un estudio de conectividad funcional basado en EEG, aplicado a sujetos de cuatro grupos de actores que completaron una Prueba de Asociación Implícita que mide el prejuicio hacia víctimas o combatientes. Analizamos siete medidas de conectividad funcional calculadas en seis bandas de frecuencia y dos condiciones experimentales diferentes. En la tarea conductual, hallamos que las víctimas tienen mayor prejuicio hacia ellas mismas, mientras los civiles tienen mayor prejuicio hacia los combatientes. También encontramos diferencias en algunas medidas de víctimas y exparamilitares con respecto a los civiles y exguerrilleros, en la banda theta, y de víctimas y exguerrilleros con respecto a los exparamilitares, en la banda beta2. Estos resultados nos ayudan a diseñar intervenciones sociocognitivas más eficaces para reducir los prejuicios.

Keywords.
Functional connectivity, EEG, Theta Rhythm, Beta Rhythm, Colombian Armed Conflict.

Palabras Clave.
Conectividad funcional, EEG, ritmos theta, ritmos beta, conflicto armado colombiano.

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1. Introduction

Colombia has had the most prolonged armed conflict, with the most victims in Latin America (Comisión de la Verdad, 2022). Since the beginning of the century, multiple efforts have been made to end it, such as the peace agreements with the paramilitaries in 2002 (Congreso de la República de Colombia, 2005) and the peace agreement with the FARC guerrillas in 2016 (Alto Comisionado para la Paz, 2016). Within this framework, different institutions have aimed to achieve reconciliation between the warring parties and reconstruct the social fabric. They have obtained mixed results, among many other reasons, because prejudices —which are evaluations of or affective responses towards a social group and its members, based on preconceptions (Amodio, 2014)— persist among the former actors of the conflict, as has happened with other armed conflicts in the world (Bar-Siman-Tov, 2004). Consequently, it is necessary to characterize this prejudice to design more effective psycho-social intervention strategies to achieve reconciliation (Ugarriza et al., 2019).

Measuring and characterizing prejudice is challenging because people usually try to hide it. Therefore, employing tools based on direct measures and explicit questions is not a successful assessment approach (Teige-Mocigemba et al., 2016). Instead, many authors prefer a methodology proposed by Greenwald et al. (1998) to assess implicit psychological processes, known as the Implicit Association Test (IAT), in which those cognitive operations are less prone to distortions due to self-image and socially desirable responses (Teige-Mocigemba et al., 2016).

The IAT aims to capture the divergence between what people say and what they think by associating concepts with valence assessments or stereotypes. It assumes that answers become more comfortable when concepts and valence assessments are closely related in the individual's mind and share the same answer key. In other words, when they are more consistent with their beliefs (Greenwald et al., 1998). The IAT shows higher levels of reliability and better results associated with the effect size compared to other indirect approaches, making IAT suitable for measuring prejudice among groups of individuals (Teige-Mocigemba et al., 2016).

IAT has been complemented with electroencephalography (EEG) to find the neurological basis of prejudice and stereotypes. In this regard, authors have looked for correlates of prejudice based on event-related potentials (ERP; Barnes-Holmes et al., 2004), frequency or time-frequency analysis (Kato et al., 2018), and reconstruction of cortical sources (Healy et al., 2015; Schindler & Wolff, 2015). However, to our knowledge, there are no functional connectivity studies characterizing prejudice, which could evidence organizational differences in the brain networks.

Functional connectivity involves studying the statistical dependencies among neurophysiological events to understand the brain network (Friston, 2011). The brain has specialized areas for executing specific tasks. However, the synchronized participation of multiple areas is required to perform any cognitive function (Friston, 1994), as functional connections discovered between brain regions through statistical measures —such as correlation, coherence, or transfer entropy— do not necessarily indicate anatomical connections between these regions. Our purpose is to know if there are statistically significant differences in the organization of the brain network among the different groups of former actors of the Colombian armed conflict, and in case they exist, if these are consistent with the results of the behavioral test.

Prejudice involves several cognitive processes in which several brain regions participate (Amodio & Cikara, 2021). Rösler and Amodio (2022) inform of two groups of brain regions involved in prejudice: those where it originates, which include the fusiform gyrus, amygdala, ATL, striatum, and insula, and those where it is regulated or attempted to be reduced, which include the ACC and PFC.

Characterizing prejudice among actors in the Colombian armed conflict through functional connectivity would provide us with valuable information about how these networks are reorganized in prejudice events and, going forward, may help us evaluate whether psycho-social intervention strategies designed to mitigate prejudice work.

In this paper, we cover the participant characteristics, the behavioral task's design, how we collected and processed EEG signals, how we extracted network measures from these signals, and the Bayesian inference hypothesis testing method used to test and measure statistically significant differences among actor groups. The results of the behavioral and functional connectivity analyses will be presented and their implications will be discussed.

2. Materials and Methods

2.1 Participants

We conducted a study involving 92 healthy Colombian volunteers, comprising 56 males and 36 females, ranging from 18 to 70 years old (mean: 36.90, SD: 10.72). The study participants were divided into four groups based on their background: former members of guerrilla groups (ex-guerrillas: 22 participants), former members of paramilitary groups (ex-paramilitaries: 31), individuals directly exposed to or affected by violent actions (victims: 23), and individuals not directly exposed to or affected by violent actions, and who were not members of guerrilla or paramilitary groups (civilians: 16). The sample was not based on an estimate but on convenience, and the participants were directly invited by the Colombian Agency for Reintegration, key actors in the municipalities with a high number of armed conflict events, and civilians with similar demographic characteristics to the ex-combatants and victims. We excluded those with a history of severe mental disorders such as schizophrenia, epilepsy, or severe head trauma. Most psychological evaluations and EEG recordings were performed on-field in classrooms of educational institutions in municipalities of Antioquia, Colombia.

We informed the participants about the study's purpose, and they signed a consent form. The research procedures were approved by the Research Ethics Committee of Universidad del Rosario (Minute DVO005-063-CS048, February 8, 2018).

2.2 Implicit Association Test – IAT

The Implicit Association Test (IAT) is a tool designed to measure implicit bias through the analysis of reaction times (RT) when participants are presented with congruent (e.g., aligning with stereotypes) and incongruent (e.g., contradicting stereotypes) pairings (Greenwald et al., 1998). The premise is straightforward: quicker RTs for congruent associations indicate automatic ease of acceptance, signifying implicit bias, whereas slower RTs for incongruent associations suggest a cognitive struggle against ingrained stereotypes, requiring more effort to dissociate from automatic responses. The essence of the IATs effectiveness in quantifying implicit biases lies in the discrepancy between these RTs, quantified through a standardized difference known as the D-score. A higher D-score signals a stronger implicit bias favoring congruent over incongruent associations (Greenwald et al., 2003).

Given the participants' low scholar level, we used a modified version of the original IAT design introducing auditory stimuli. Figure 1 shows the test screens presented to the participants. Figure 1(A) left represents the concept of "combatant" or "armed actor" and not a specific group of the participants, and the image on the right represents the concept of "victim". The happy and sad face icons in Figure 1(B) represent positive and negative valences, respectively. The audio "Ganar" ("Win" in Spanish) is the stimulus, which must be associated with the happy face (good valence), for which the participant has up to three seconds to press the shift key on the left side of the keyboard. Figure 1(C) corresponds to the congruent block, and Figure 1(E) corresponds to the incongruent one. The IAT effect occurs when the average time to associate the stimulus with the corresponding valence in one of the configurations (congruent or incongruent blocks) is shorter than in the other. Further detailed information about the task can be found in Baez et al. (2019).

The IAT D-score was calculated as proposed by Greenwald et al. (2003) using the IAT package (Martin, 2014) of the R statistical software. The procedure used to calculate the D-score was:

1. Identify blocks for congruent task A as A1 and A2; those for incongruent task B as B1 and B2. If task A is Blocks 3 & 4, Block 3 is A1, and Block 4 is A2.
2. Eliminate all subjects for whom more than 10% of remaining trials have RT faster than 300 ms.
3. Compute RT means (MnA1, MnA2, MnB1, MnB2) and SDs (SDA1, SDA2, SDB1, SDB2) for the four blocks for all remaining trials.
4. Compute two mean RT differences: B1– A1 = (MnB1 – MnA1) and B2 – A2 = (MnB2 – MnA2).
5. Compute an inclusive (not pooled) SD1 using all RT in Blocks A1 & B1; another (SD2) using all RT for A2 & B2 (SD2).
6. Compute (B1–A1) / SD1; and (B2–A2) / SD2.
7. D-score=Average of two quotients computed in Step 6.

2.3 EEG Acquisition and Preprocessing

The IAT task was synchronized with EEG recordings acquired with a 64-channel Biosemi ActiveTwo with a sampling frequency of 2048 Hz. The electrodes were placed according to the international 10-20 system using quick-caps, and impedances were kept below 10 k. The EEG device and the laptops worked with batteries while recording to avoid electric issues.

EEG recordings were preprocessed using the MNE-Python package (Gramfort, 2013). The preprocessing pipeline used to obtain the Even-Related Potentials (ERP) was then:

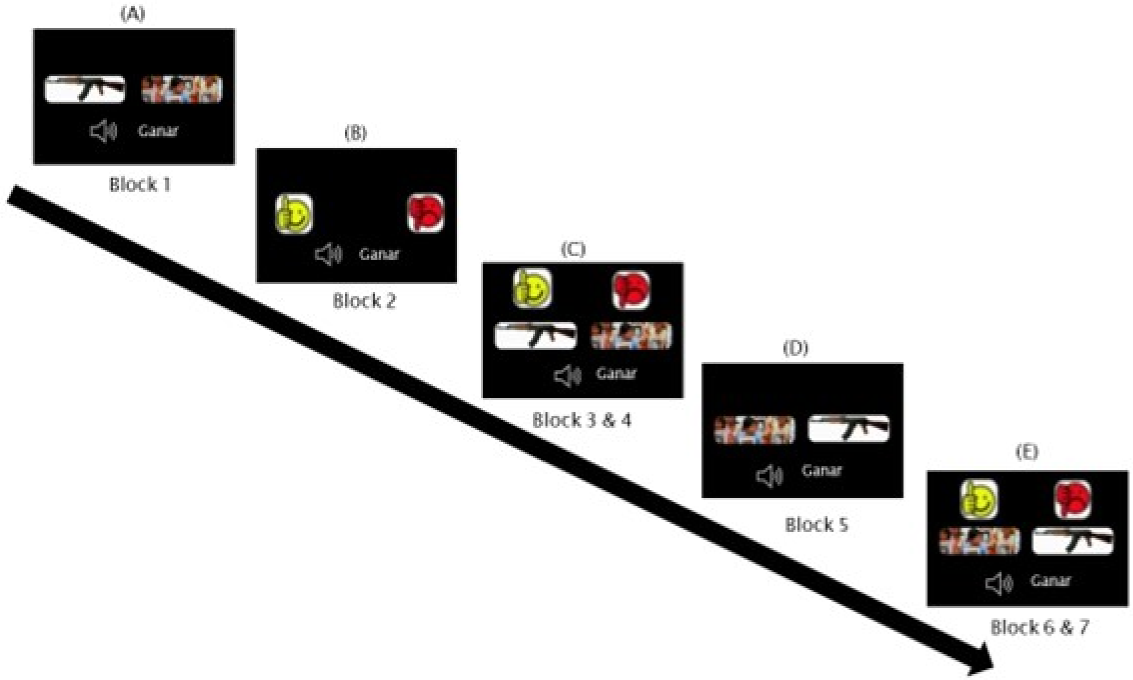
1. Montage selection.
2. High-pass filtering (with a zero-phase FIR filter) with a cut-off frequency of 1 Hz.
3. Detection, elimination, and interpolation of bad channels using the `pyprep` library (Bigdely-Shamlo et al., 2015).
4. Offline re-referencing using the Reference Electrode Standardization Technique (REST) (Yao, 2001).
5. Independent components' analysis.
6. Partition of EEG signals in epochs between −200 and 800 ms around the stimuli.
7. Baseline correction to each epoch and channel individually in the following way: (i) Calculate the mean signal of the baseline period. (ii) Subtract this mean from the entire epoch.
8. Decimation by eight, equivalent to subsample at 256 Hz.
9. Selection of IAT congruent and incongruent blocks' trial epochs (60 trials for each block).
10. Correction of bad epochs with the `Autoreject` library (Jas et al., 2017).
11. Low-pass filtering with a cut-off frequency of 40 Hz.

2.4 EEG-based Functional Connectivity

Functional connectivity is a set of techniques based on graph theory, which aims to measure the synchronization among brain regions, assuming that brain functions require the coordinated participation of several ones (Poli et al., 2015). The first step to making EEG-based functional connectivity analyses is to build the connectivity matrices that reveal how synchronized the sensed signals are. In this study, we used the Debiased estima-

Figure 1

IAT pipeline



Note. Schematic representation of the time course of events within an IAT experiment, illustrating the sequence of blocks including concept (blocks 1 and 5) and valence (block 2) practice; congruent practice (block 3) and test (block 5); and incongruent practice (block 6) and test (block 7) blocks.

tor of the squared Weighted Phase Lag Index (Vinck et al., 2011) to build the connectivity matrix, which, according to Bastos and Schoffelen (2016), is better than other measures because it is insensitive to the volume conduction problem, and is not affected by the bias produced by the difference in sample size between conditions. This measure was applied to the spectrum of the sensed signals, which was estimated using the multitaper method. In our study, we built connectivity matrices for each subject's ERP and IAT block (congruent and incongruent) on the following frequency bands: Delta (0 – 4 Hz), Theta (4 – 7 Hz), Alpha (7 – 13 Hz), Beta1 (13 – 20 Hz), Beta2 (20 – 30 Hz), and Gamma (30 – 40 Hz).

Once the connectivity matrices were obtained, we extracted the Minimum Spanning Tree (MST) for each using the Kruskal method (Kruskal, 1956). An MST is a tree structure that spans all nodes in a connected, undirected graph while minimizing the sum of edge weights. In other words, an MST is a subnetwork that connects all nodes without forming cycles and has the smallest possible total edge weight (Kruskal, 1956; Prim, 1957). This method was preferred since there still needs to be a consensus on the right way to choose threshold values, which has led to contradictory results (Stam et al., 2014; Zakharov et al., 2020). The advantages of using MST are that the weighted connectivity matrix is unique, connections may be binarized to avoid density effects, the number of links in the MST is fixed, MST measures can be interpreted along the lines of conventional metrics that characterize network topology (Stam et al., 2014), and it is relatively insensitive to bias and noise (Tewarie et al., 2015). It allows studies with MST to be comparable (Blomsma et al., 2022).

Then, for each subject per block and frequency band, the following global network measures were calculated:

Leaf fraction. The fraction of nodes with only one connection. The higher it is, the more the MST will resemble a star, and communication will depend more on central nodes (hubs) (Cao et al., 2020). This measure's minimum value is 2/M, where M is the number of links, and the maximum is 1.

Diameter. The longest distance between any two nodes in the network. This measure is normalized by dividing it by the number of links. It measures network efficiency, understood as the ability to transmit information between nodes more directly, with less noise, attenuation, and interference (Rubinov & Sporns, 2010).

Mean eccentricity. The node's eccentricity is the longest optimal path from this node to any other node (Stam et al., 2014). Low levels of mean eccentricity mean that MST nodes are close to hub nodes.

Maximum degree. The maximum degree of all nodes.

Betweenness centrality. The fraction of the shortest paths that pass through a particular node (Fornito et al., 2016). The maximum value of this measure is used as a global measure (Cao et al., 2020) and interpreted as indicative of how centralized the network is. Degree, eccentricity, and betweenness are measures that quantify node centrality.

Tree hierarchy. This measure quantifies the trade-off between large-scale integration in the MST and the overload of central nodes (Cao et al., 2020). It characterizes a hypothetical, optimal topology of an efficient organization while preventing information overload of central nodes (van Dellen et al., 2018). For a line topology, the tree hierarchy is 2/M; for a star topology, the tree hierarchy is .5. The tree hierarchy has values between 2/M and 1 (Stam et al., 2014) for topologies between these extreme configurations.

2.5 Hypothesis Testing by Bayesian Inference

Bayesian inference provides a robust alternative to traditional frequentist methodologies, explicitly addressing the issues associated with reliability and reproducibility (Keysers et al., 2020; Wagenmakers et al., 2018). This approach offers a mechanism to ascertain the presence and magnitude of an effect (van Doorn et al., 2021). In this context, the Bayes factor measures the comparative predictive accuracy between two competing hypotheses (i.e., null and alternative). It delineates how much the observed data shifts the beliefs regarding the respective likelihoods of these hypotheses, expressed in Eq. 1:

$$BF_{10} = \frac{p(D|H_1)}{p(D|H_0)} \tag{1}$$

where $p(D|H_1)$ represents the evidence supporting the alternative hypothesis, and $p(D|H_0)$ denotes the evidence backing the null hypothesis (Etz & Vandekerckhove, 2018). The Bayes factor notation identifies which hypothesis receives endorsement from the data. BF_{10} indicates the Bayes factor favoring of H_1 over H_0, while BF_{01} indicates the Bayes factor favoring H_0 over H_1. Specifically, $BF_{10} = 1/BF_{01}$. Larger values of BF_{10} indicate more support for H_1. Values for Bayes factors span from 0 to ∞, with a factor of 1 suggesting equal predictive power from both hypotheses (van Doorn et al., 2021).

When using Bayesian analysis, variance comparisons are like comparing linear regression models. The predictors used in this analysis include the various factors and their interactions with a null model that has no predictors but does include an intercept (Wetzels et al., 2012). It compares potential models to the null model using Bayes factors to determine which model best fits the data. Analyzing each factor alone can help decide whether or not to include it in the model (Wagenmakers et al., 2018). It is important to only conduct post-hoc analyses for necessary factors in the model. These analyses require adjustments for multiple comparisons, which can be achieved using the methodology explained by Jeffreys (1938) or Westfall et al. (1997).

Plotting the posterior distribution and calculating the $x\%$ credible interval (CI) is recommended to determine the effect size. The posterior distribution reflects the updated likelihood of parameter values after a priori knowledge is considered alongside the data. The CI contains the percentage of the mass of the posterior distribution. Two popular methods of creating a CI are the highest density CI, which is the narrowest interval containing the specified mass, and the central CI, which involves cutting off $\frac{100-x}{2}$ from each tail of the posterior distribution (van Doorn et al., 2021).

Considering the explanation above, the following analyses were performed for each MST measure/frequency band combination:

- Mixed ANOVA, taking the block type (congruent or incongruent) as a within-subjects factor and the network measure as a between-subjects factor. As a priori parameter, we will consider a small effect size (Cohen's $d = .25$).
- One-way ANOVA, taking the difference between congruent and incongruent network measures block as a dependent variable. As a priori parameter, we will consider a small effect size (Cohen's $d = .25$).
- Post hoc analysis for those factors or interactions considered relevant in the models, adjusting the priors according to Westfall's procedure (Westfall et al., 1997) to correct for multiple comparisons.

3. Results

3.1 Behavioral Results

For the IAT D-score, the best-fitting model explaining the observed mean amplitudes includes measures of the actors' group ($Bf_M = 2.466$, $BF_{null} = .405$). There is strong evidence in favor of the hypothesis that the IAT D-scores of the victims tend to be more positive than those of civilians (BF=10.838) and ex-guerrillas ($BF = 8.977$). Table 1 displays the descriptive statistics and 95% credible intervals for each actor group's IAT D-score posterior.

3.2 3.2 Functional Connectivity Results

Statistically significant differences were found in the theta and beta2 bands. No effect was found in any other band. The effects found are presented below.

3.2.1 Theta Band

We found differences in the mean diameters and eccentricity between congruent and incongruent blocks. For diameter, the model that best explains the data is the one that includes the actor group as a factor ($BF = 11.663$), and the post hoc analyses showed that there is moderate evidence in favor of the hypotheses that victims' differences are more positive than the ex-guerrillas' differences ($BF = 5.020$) and civilians' differences ($BF =$

Table 1

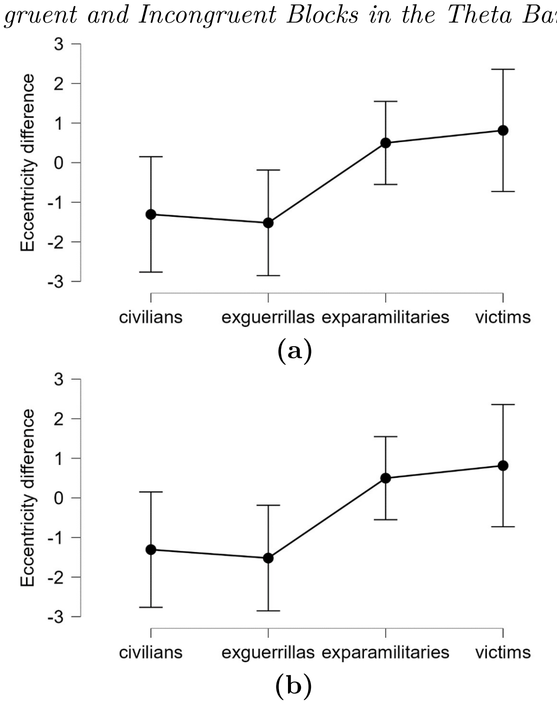
Statistics IAT D-Score

Actor's group	Mean	SD	N	95% CI	
				Lower	Upper
Civilians	−.121	.355	15	−.317	.076
Ex-guerrillas	−.031	.233	22	−.135	.072
Ex-paramilitaries	.049	.381	31	−.091	.189
Victims	.185	.252	23	.076	.294

3.703). We also found moderate evidence in favor of the hypothesis that the ex-paramilitaries' differences are more positive than the ex-guerrillas' differences ($BF = 6.854$) and civilians' differences ($BF = 11.847$). Finally, we found moderate evidence that the ex-paramilitaries' and victims' differences are similar ($BF = 0.285$) and that the civilians' and ex-guerrillas' differences are similar ($BF = .323$). The point plot, Figure 2(a), shows that for victims and ex-paramilitaries, the congruent block's mean diameters are larger than those of the incongruent block. In contrast, for civilians and ex-guerrillas, the mean diameters of the congruent block are smaller than those of the incongruent one.

Figure 2

Point Plots of (a) Differences between Diameter Means of Congruent and Incongruent Blocks, and (b) Differences between Eccentricity Means of Congruent and Incongruent Blocks in the Theta Band



Note. For victims and ex-paramilitaries, the mean diameters and eccentricities of the congruent block are larger. As a result, the differences tend to be positive. In contrast, for civilians and ex-guerrillas, the differences tend to be negative.

For eccentricity, the model that best explains the data is the one that includes the actor group as a factor ($BF = 3.038$). The post hoc analyses showed moderate evidence in favor of the hypothesis that ex-paramilitaries' differences are more positive than ex-guerrillas' ones ($BF = 3.255$). We also found moderate evidence that ex-paramilitaries' and victims' differences are similar ($BF = .292$) and that civilians' and ex-guerrillas' differences are similar ($BF = .329$). The point plot in Figure 2(b) shows that for victims and ex-paramilitaries, the mean diameters of the congruent block are larger than the ones of the incongruent block. In contrast, for civilians and ex-guerrillas, the mean diameters of the congruent block are smaller than those of the incongruent one.

3.2.2 Beta2 Band

We observed effects in the mean diameter and mean eccentricity (and their differences) between congruent and incongruent blocks. For diameter, the model that best explains the data is the one that includes the actor group as a factor ($BF = 5.230$), and the post hoc analyses showed that there is moderate evidence in favor of the hypotheses that ex-paramilitaries' differences are more negative than the ex-guerrillas' differences ($BF = 7.849$) and victims' differences ($BF = 6.427$). Additionally, we found moderate evidence that the ex-guerrillas' and victims' measures are similar ($BF = .292$).

Concerning the mean diameter in the incongruent block, the model that best explains the data is the one that includes the actor group as a factor ($BF = 48.582$), and the post hoc analyses showed that there is strong evidence in favor of the hypotheses that ex-paramilitaries' diameters are more positive than the ex-guerrillas' diameters ($BF = 29.619$) and victims' diameters ($BF = 44.733$). Additionally, we found moderate evidence that the ex-guerrillas' and victims' diameters are similar ($BF = .322$).

The point plot (Figure 3(a)) shows that for victims and ex-guerrillas, the mean diameters of the congruent block are larger than the mean diameters of the incongruent one. In contrast, for civilians and ex-paramilitaries, the mean diameters of the congruent block are smaller.

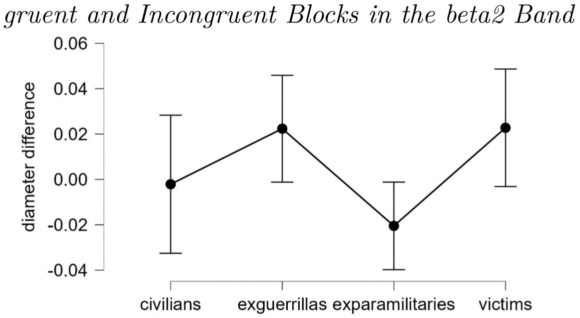
Regarding eccentricity, the model that best explains the data is the one that includes the actor group as a factor ($BF = 3.455$). The post hoc analyses showed that there is moderate evidence in favor of the hypotheses that ex-paramilitaries' differences are more positive than ex-guerrillas' differences ($BF = 7.001$) and victims' differences ($BF = 3.894$). We also found moderate evidence that ex-guerrillas' and victims' differences are similar ($BF = 0.297$).

For the mean eccentricity in the incongruent block, it was found that the model that best explains the data is the one that includes the actor group as a factor ($BF = 16.856$), and the post hoc analyses showed that there is strong evidence in favor of the hypotheses that ex-paramilitaries' eccentricities are more positive than the ones of ex-guerrillas ($BF = 10.099$) and victims ($BF = 23.325$). Additionally, we found moderate evidence that the ex-guerrillas' and victims' diameters are similar ($BF = .334$).

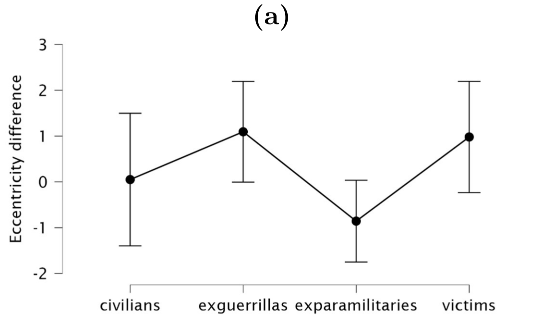
The point plot, Figure 3(b), shows that for victims and ex-guerrillas, the mean eccentricities of the congruent block are larger than those of the incongruent one. In contrast, for civilians and ex-paramilitaries, the mean eccentricities of the congruent block are smaller.

Figure 3

Point Plots of (a) Differences Between Diameter Means of Congruent and Incongruent Blocks, and (b) Differences Between Eccentricity Means of Congruent and Incongruent Blocks in the beta2 Band



(a)



(b)

Note. The plots include 95% credible intervals. For victims and ex-guerrillas, the mean diameters and eccentricities of the congruent block are larger. As a result, the differences tend to be positive. Conversely, for ex-paramilitaries, the differences tend to be negative. Finally, for civilians, the differences tend to zero.

4. Discussion

This study used EEG-based sensor-level functional connectivity to characterize an IAT designed to measure prejudice among former actors of the Colombian armed conflict. To our knowledge, this is the first study using this technique to characterize prejudice. It provided relevant information about how different brain regions are synchronized in time and phase when social bias events occur and whether different patterns of neural rhythms can be observed.

Behavioral results indicate that civilians are more inclined to be more prejudiced toward ex-combatants than victims. Ex-guerrillas and ex-paramilitaries appear to exhibit no prejudice toward victims or themselves, and victims are more inclined to be prejudiced toward their group. Although this seems to go against common sense, many reported cases of prejudice towards the same group exist. For example, March and Graham (2014) showed in a study that Hispanic women are biased toward their group concerning the white women's group; Newheiser et al. (2014) and Gedeon et al. (2021) have reported cases in which children of low economic status show bias against their group in favor of children of high economic status.

Biases towards the same group could be explained under the Social identity theory (Tajfel et al., 1979) approach, which primarily discusses how people derive self-esteem from group memberships and favor their group. While the focus is on outgroup discrimination, the underlying mechanisms also offer insight into why and when ingroup prejudice might occur. Another approach to ingroup bias is the system justification theory (Jost et al., 2004). It addresses how and why people, including disadvantaged group members, sometimes support and legitimize social systems that disadvantage them.

Statistically significant differences were found in the theta and beta2 bands. In the theta band, the mean diameter and eccentricity of the congruent block of victims and ex-paramilitaries tended to be greater than those of the incongruent block. Greater diameters and eccentricities are indicative of a more efficient network in transmitting information (van Dellen et al., 2018), given that the MST tends to be more centralized (star-like shape) and less linear-like (Stam et al., 2014; Tewarie et al., 2015). Theta rhythms have been associated with executive function and cognitive control (Cavanagh & Frank, 2014), and it has been detected that these rhythms increase when a surprising or unpleasant stimulus is received (Smit et al., 2023). Therefore, a reasonable explanation is that for ex-paramilitaries and victims, the stimuli of the incongruent block are more opposed to their preconceptions than the stimuli of the congruent block, which would reflect a bias towards victims. On the other hand, given that the diameter and eccentricity of the incongruent block of civilians and ex-guerrillas tend to be greater than those of the congruent block, it could be inferred that they make a greater effort to respond to the congruent stimuli, and that this reflects a bias towards ex-combatants.

In the beta2 band, the mean diameter and eccentricity of the congruent block of victims and ex-guerrillas tended to be larger than in the incongruent block, which, following the same reasoning of the previous paragraph, would indicate that for these groups the networks of the congruent block are more efficient than those of the incongruent one. Böttcher et al. (2023) state that beta rhythm is mainly associated with sensorimotor processing. On the other hand, Beste et al. (2023) found that the amplitude of beta oscillations in sensorimotor areas decreases just before and during movement execution. Conversely, an increase in beta amplitude above baseline levels is observed after movement execution, known as post-movement event-related synchronization -ERS. Beta oscillations tend to vary during movement. Generally, movements decrease beta activity, while successful movement cancellation typically increases beta activity. Therefore, beta ERS is believed to reflect an active inhibition of the motor cortex by somatosensory feedback. For victims and ex-guerrillas, lower efficiency in the incongruent block in this band may reflect greater inhibition to respond correctly to these stimuli.

Given that we have previously conducted socio-cognitive interventions with former actors of the Colombian armed conflict, designed to improve emotional processing (Valencia et al., 2020) and reduce aggressiveness (Trujillo et al., 2017), the results of this research are valuable input for customizing and improving these strategies, always aiming to reduce prejudice and achieve reconciliation between former enemies (Ugarriza et al., 2019).

5. Conclusions

The functional connectivity analysis indicates that civilians and ex-guerrillas tend to generate more prejudice toward armed actors than toward victims, which is also reflected in the behavioral test. Following this same reasoning, it seems that victims and ex-paramilitaries tend to generate more prejudice toward victims. On the other hand, ex-guerrillas and victims tend to regulate their prejudice toward victims better. Similarly, the ex-paramilitaries seem to regulate their prejudice toward combatants better. Finally, it seems that civilians regulate prejudice toward victims and combatants similarly.

Putting these results together, we found that victims generate more bias toward themselves, while ex-paramilitaries were found to generate more bias toward victims. With the ex-guerrillas, the opposite occurs: they generate more prejudice towards combatants but tend to regulate the prejudice towards victims. Finally, civilians showed more prejudice towards combatants and similarly regulated prejudice towards victims and combatants.

There is still a need for broader analyses to understand the neurological and cognitive implications of the results found. Future work should investigate whether some measure of functional connectivity may constitute an electrophysiological correlate of some social bias. Based on the results, the measures of diameter and eccentricity in the theta and beta2 bands seem promising. Another possible line of research is connecting these results with EEG-ERP and source-level functional connectivity (e.g., fMRI).

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